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Quantifying the Effect of Commercial Transportation Practices in Military Supply Chains

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FOR THE COMMANDER

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14. ABSTRACT

This research examines the Multi-Indenture Multi-Echelon (MIME) repairable inventory system used by the United States Air Force, reviews the literature documenting successful commercial practices that have been implemented in similar supply chains, and documents the metrics used in private industry to assess supply chains. Using simulation, this research assesses the effect of applying such commercial practices to military supply chains, and then evaluates the results by using private industry metrics in coordination with metrics currently used by the Air Force.

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Contents

Figures

Tables

Acronyms

AF	Air Force
AFRL	Air Force Research Laboratory
AFRL/HEAL	AFRL/Human Effectiveness Logistics Readiness
AMC	Air Mobility Command
B.S.I.E.	Bachelor of Science in Industrial Engineering
CDRL	Contract Data Requirements List
CONUS	Continental United States
CWT	Customer Wait Time
EDA	Equipment Downtime Analyzer
EDD	Earliest Due Date
ELT	Emergency Lateral Transshipment
FIFO	First In First Out
HVI	High Velocity Infrastructure
LRU	Line Replaceable Unit
LTL	Less than Truck Load
LTS	Lateral Transshipment
MC	Mission-Capable/Mission Capability
MDT	Maintenance Down Time
METRIC	Multi-Echelon Technique for Recoverable Item Control
MICAP	Mission-Impaired Capability Awaiting Parts
MIME	Multi-Indenture Multi-Echelon
MTBM	Mean Time Between Maintenance
MTTF	Mean Time to Failure
NMC	Non-Mission-Capable

OCONUS	Outside Continental United States
OST	Order Ship Time
PCO	Percent making Cut-Off
P.E.	Professional Engineer
Ph.D.	Philosophiae Doctor (doctor of philosophy)
PI	Phase Inspection
RWT	Requisition Wait Time
SPT	Shortest Processing Time
SRU	Shop Replaceable Unit
TL	Truck Load
TTF	Time To Failure
UPS®	United Parcel Service®
USPS®	United States Postal Service®
VM	Velocity Management
VTMR	Variance-to-Mean Ratio

Executive Summary

Military supply chains encompass a complicated network of suppliers and customers, who deal with a wide variety of items. These items can range from complete weapon systems and repairable items to non-repairable consumables. Demand inside the network is generated at the military unit level at a specific base. The demand from the base is aggregated to military service depots, which comprise the retail level in the network. The service depots are supplied by either military wholesalers or commercial wholesalers, such as the Defense Logistics Agency and direct vendors. These many layers of the supply chain often result in unnecessary cost and delay times, as well as low network reliability. Better integration among the multiple levels of the supply chain may be achieved through the effective use of different transportation modes and criterion. Traditional multi-echelon inventory and readiness-based models have not fully examined the ability of effective transportation use to reduce cost, delay times, and improve readiness in the overall military logistics network. Uncertainty also surrounds the question of how the military logistical network structure might need to change to take full advantage of various transportation options. In this research project, we develop a simulation-based methodology for quantifying the effect of transportation options (that is, truckload shipping, less-than-truckload shipping, transshipments, and express air shipping) on shipping costs, customer wait times, abort rates, and operational availability.

For the purposes of this report, a simulation model was developed based upon the Air Force's Multi-Indenture Multi-Echelon (MIME) repairable parts system. This simulation model encompasses a structure that includes 24 individual shop replaceable units (SRUs) composing six line replaceable units (LRUs), 432 aircraft, six bases, and one depot. The experiments outlined in *Section 5* were designed to provide information about the largest contributing factors associated with Operational Availability, Abort Rate, Customer Wait Time, and Total Transportation Cost. Eleven factors were chosen to be varied in this experiment (*Table 5.1*). To explore how each factor, along with its interactions, affected the four indicators of model performance, a fractional factorial experimental design was used. With this experimental design, there were 128 individual design points, each of which was replicated five times, yielding a total of 640 simulation runs. The information provided by these simulation runs allows the creation of linear response surface regression models for each response. The regression models provide the ability to evaluate the effect each factor has on each response.

A second set of experiments was completed in an attempt to find the most appealing combination of factors. For each design point, the four response values were scaled to be between zero and one, weighted by importance, and added together yielding a utility value. The utility value provides a mechanism to compare the 128 design points. From the 128 design points, the top nine were chosen based upon utility, and a second set of 65 replications was run for each of the nine. The second set of experiments provided statistical information on the best performing combination of factors based upon utility. The findings of our experiments are as follows:

- Mission Impaired Capability Awaiting Parts (MICAP), Time to Failure (TTF), Local Repair, Shipping Option, Sortie Duration, and Inventory Position were the most influential factors in affecting the values of Operational Availability, Abort Rate, Customer Wait Time, and Total Transportation Cost
- Reliance on MICAP overshadows the other transportation cost components
- Reliance on MICAP hides many problems within the supply chain
- A combination of altering the amount of repair resources allocated to the base level and the amount of inventory at the base level provides an opportunity for improving system performance
- Different shipping strategies (such as Less than Truck Load [LTL], Truck Load [TL], and Emergency Lateral Transshipment [ELT] can induce significant system improvement and warrant future study

This research has resulted in significant insights into the operation of commercial logistics within the Air Force MIME supply chain. In addition, this research has yielded the following products:

- A conference article discussing the simulation is planned for the Winter Simulation Conference military track for the 2004 conference in Washington, D.C.
- One or two journal articles will be written, based upon the results of this report, and submitted to the *Air Force Journal of Logistics*

1 Military Logistics and the MIME Repairable Inventory System

Since the end of the Cold War, military budgets have been declining drastically, and the Department of Defense's logistical system has been asked to be more flexible and responsive with less money. In the past, they have met their needs by relying on massive inventories. But the Department of Defense now seeks to implement quicker, more agile logistics systems that will reduce the inventory dollars on hand (Condon 1999). To this end, the Armed Forces have undertaken a variety of initiatives, such as Lean Logistics and Velocity Management (VM), to improve responsiveness and reduce the total cost of inventory by decreasing logistics pipeline times. For years, the Armed Forces' logistical systems have lagged behind the best commercial practices. Within private, multi-echelon inventory systems similar to that of the military's, commercial practices such as scheduled truck deliveries and lateral shipments have significantly reduced the need for inventory stockpiles by reducing pipeline times along with customer wait times.

This research examines the MIME repairable inventory system used by the United States Air Force, reviews the literature documenting successful commercial practices that have been implemented in similar supply chains, and documents the metrics used in private industry to assess supply chains. Using simulation, this research assesses the effect of applying such commercial practices to military supply chains, and then evaluates the results by using private industry metrics in coordination with metrics currently used by the Air Force.

1.1 MIME Repairable Inventory System

For our research, we are examining a MIME repairable inventory system. Multi-echelon refers to the fact that inventory is kept and repaired at multiple levels in the supply chain (that is, depot, bases, and weapons). This structure can be seen in *Figure 1.1*. Multi-indenture refers to the fact that each repairable component in inventory is comprised of multiple subcomponents that may in turn be comprised of further subcomponents (*Figure 1.3*).

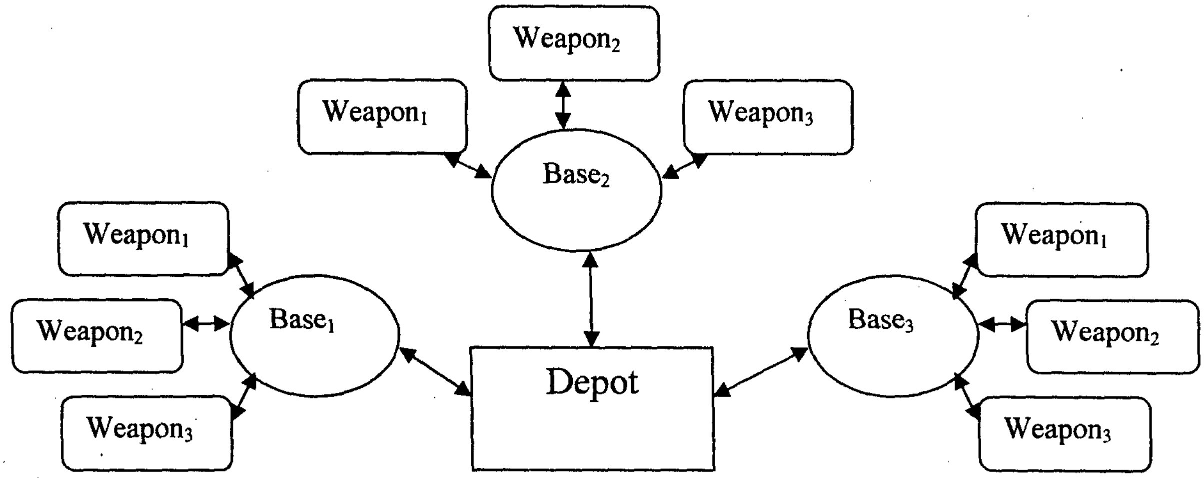

Figure 1.1: Multi-Echelon System

Figure 1.1 depicts a depot that supports three bases (Base$_1$, Base$_2$, Base$_3$), each of which supports three weapon systems (Weapon$_1$, Weapon$_2$, Weapon$_3$). This system can be expanded, in theory, with additional bases, weapons, and depots. It is also common for several depots to be serviced by one common vendor (*Figure 1.2*); however, for the purposes of this research the relationship between the depots and vendors will not be analyzed. Our simulation and analysis will only consider the structure presented in *Figure 1.1.*

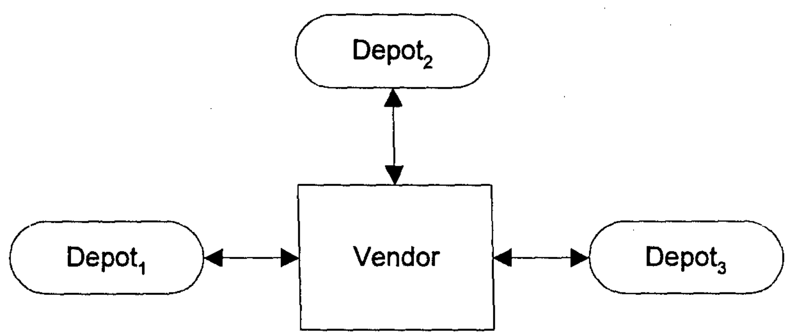

Figure 1.2: Addition of Vendor to System

For this research, a weapon is conceptualized as an aircraft. Each weapon is made up of multiple components called LRUs, shown in *Figure 1.3*. LRUs are made up of multiple sub-components called SRUs. In *Figure 1.3,* the subscript *i* denotes the LRU for which the SRU is a subcomponent, while *j* denotes the SRU type.

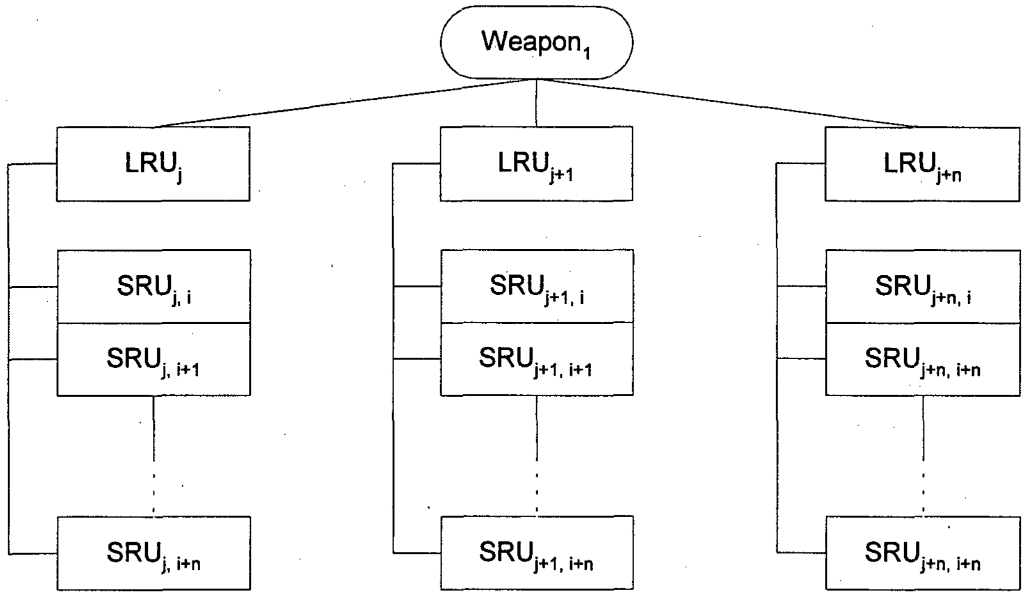

Figure 1.3: Hierarchy of Weapon System

As the two-way arrows in *Figure 1.1* imply, the depot, base, and weapon all exchange inventory. When a weapon failure occurs, the faulty SRU is swapped with a working part at the base. The failed part may be repaired at the base or may be sent back to the depot for repair. If it is sent to the depot for repair, the depot will send a working part to the base to replenish the base's inventory. In other words, the inventory policy used in this system is the base stock policy or one-for-one policy. Spare parts inventory, especially at the LRU level, often contains high-cost, low-demand items. In the base stock policy, the inventory position (on hand + on order – backlog) is always kept at the same order up to level, say S. In a base stock policy, when a demand occurs for the item, the inventory position will drop below S, which triggers a replenishment order of a quantity of one.

1.2 Mission Capability

The goal of a military MIME system is to maximize the mission capability (MC) of the weapon:

$$MC = \frac{uptime}{uptime + downtime} = \frac{MTBF}{MTBF + MDT}$$

Equation 1.1

In Equation 1.1, MTBM is the mean time between maintenance and MDT is the maintenance down time. From this equation, it is evident that the only ways to improve mission capability are to increase MTBM (the weapon's reliability) or decrease MDT (that is, repair time) (Kang *et al.* 1998).

A weapon incurs downtime when one of its LRUs fails. An LRU fails when one of its SRUs fails. When a failure occurs, the failed SRU is removed from the aircraft and sent to repair. Each base has a limited repair facility for failed parts and a warehouse to store a limited amount of inventory. The typical failure cycle of a simple, single echelon base is shown in *Figure 1.4*. Note that every spare part shown is not necessarily the same part that originally failed. The representation of the failure cycle and repair process becomes more complicated than that depicted in *Figure 1.4* when we move to a MIME system.

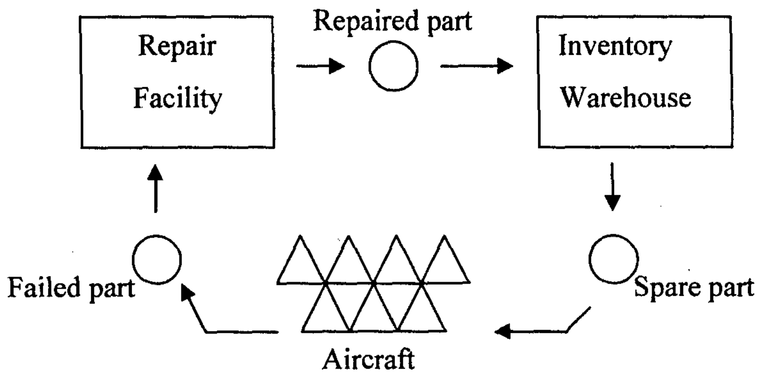

Figure 1.4: Failure Cycle and Repair Process

1.3 Failure Cycle, Repair Process and Inventory Levels

The failure of a weapon initiates the failure cycle. Again, a weapon fails when one or more of its LRUs fail, and an LRU fails when one or more of its SRUs fail. Thus, the initial failure event is the failure of an SRU.

For our system, LRUs and SRUs are the only recoverable (that is to say, repairable) parts. This means an attempt is always made to repair an LRU or SRU. Failed LRUs and SRUs can be repaired at the base or depot level. As only a small percentage of failed SRUs can be repaired at the base level, the majority of them are sent to the depot for repair. Subcomponents of an SRU, called "bits and pieces," are consumables and will not be considered for repair. Since our model is tailored to avionics items, two levels of indenture will suffice (Miller 1992). A weapon is repaired by repairing the failed LRUs, or by filling the holes of the weapon. Similarly, a failed LRU is repaired (at the base or depot) by replacing its failed SRUs with functional SRUs. Finally, a failed SRU is repaired at the depot by servicing and repair.

When avionic faults are noted on a weapon, flight line technicians attempt to diagnose the problems and identify the failed LRU. When this is determined, the faulty SRUs are removed from the weapon and sent to an intermediate repair shop, thus initiating the repair process. The first decision that must be made in the repair process is where the SRUs will be repaired. Will repair occur at the base or depot? The base may not be able to perform the necessary repair for several reasons (Miller 1992):

- Some bases, particularly those with few weapons, are not equipped to repair LRUs
- Though some bases may be equipped to repair certain types of LRU failures, the necessary repair may be beyond their capabilities
- The base may not be authorized to repair a particular type of LRU

If any one of these is the case, the base sends the SRU to the depot for repair. In the model, the determination of where the part can be repaired is dictated by a percentage set by the user. In the base case of the model, 1% of all failures can be repaired at the base level.

1.3.1 LRU Repair at the Base Level

As described above, the failed LRU is removed from the weapon and sent to an intermediate repair shop. At test stations, technicians perform a battery of tests to determine the problem. Sometimes, the LRU can be fixed by straightening pins, cleaning connections, replacing fuses, re-soldering connections, or recalibrating. But often, tests reveal that repair requires the replacement of a failed SRU. Once the defective SRU is determined, two things can happen:

- If a spare SRU is available in the base's inventory, the defective SRU is swapped with the spare. The defective SRU is either repaired at the base level and put back into inventory or is sent to the depot for repair. If the SRU is sent to the depot for repair, an order is generated for the part.
- If a spare SRU is unavailable in base inventory, the defective SRU is sent to the depot for repair and an order is generated for this part. The order is marked to indicate that the aircraft from which the defective SRU was removed is MICAP. This designation indicates that express-air shipping will be used.

In both scenarios, base-level repair is characterized by swapping the failed SRU with a serviceable SRU, called filling the LRU hole. Also, in either case, if a defective SRU is sent to the depot for repair, an order corresponding to that SRU type is sent to the depot. The order is filled from depot inventory and shipped back to the base to replenish its inventory.

1.3.2 SRU Repair at the Depot Level

If a base cannot repair a failed SRU, the base sends it to the depot for repair. Upon receipt of an SRU from a base, the depot will send the base a serviceable SRU. The SRU received from the base will be inducted into the depot's repair process and upon repair will be retained in the depot's inventory

The depot tries to maintain a constant level of inventory for itself and the bases, in keeping with the aforementioned base stock inventory policy. From the depot's standpoint, whenever a defective part is received, a serviceable part is shipped. Similarly, from the base's standpoint, whenever a defective part is shipped, a serviceable part is received.

1.4 Complicating Possibilities or Assumptions

The literature regarding the MIME inventory system (namely the models built on Sherbrooke's Multi-Echelon Technique for Recoverable Item Control [METRIC] [1968] and Muckstadt's MOD-METRIC [1973]) makes a number of simplifying assumptions. These assumptions include:

- Repair Facility Capacity—Traditional literature assumes unlimited repair capacity at each repair facility. In reality, if the available repair resources are busy, the failed part must wait in queue to be repaired. It may be preferable to send a part to the depot or another base for repair if long queues can be avoided or limited capacity exists at the repair facility.
- Repair and Ordering Policy—Most analytical MIME inventory systems assume a continuous review, or (S-1) ordering policy; however, in reality, both orders and repair jobs are batched to reduce transportation and set-up costs. This can significantly affect process and pipeline times.
- Base/Depot Repair Characteristics—The literature assumes each repair facility has the same repair capability; however, some bases may be equipped for repairing only certain types of SRUs. Allowing bases and depots to have different repair facilities and capabilities could significantly affect where parts are sent for repair.
- Cannibalization—Cannibalization is the use of functioning spare parts from an already-failed weapon on a base. Sherbrooke's METRIC (1968) does not address cannibalization; however, this practice may provide a way to utilize a base's available inventory effectively.
- Prioritized Repair—Most traditional MIME models assume a "first-in first-out" (FIFO) policy at the repair facility; however, repair cycle times for high-priority parts could be reduced if those parts are given preference in a queue.

1.5 Transportation Considerations

The MIME inventory and repair system must also account for the transportation of parts between depots and bases. There are two traditional ways for shipping parts: TL and LTL. Truckload shipments require full loads and are usually less expensive than LTL shipments. LTL shipments are characterized by smaller batch sizes; therefore, more shipments are made. LTL shipping is more responsive to fluctuations in demand, but tends to be more costly. Traditionally, parts are only shipped between the depot and the base; however, an open area of research is the use of lateral transshipments (specifically, shipments between the bases themselves). Lateral transshipments could create a more responsive system but complicate the transportation network, truck schedules, and inventory positions throughout the supply chain.

2 Literature Review of Relevant Commercial Practices

The goal of this project is to maximize the mission capability of weapon systems by minimizing weapon downtime due to repair or maintenance. The reduction of downtime for maintenance of a failed weapon can be achieved through two strategies:

- Reduce the process time of each stage associated with the repair process (that is, ordering, shipping, backordering, repair times) and thereby reduce the time a repaired or spare part spends in the pipeline
- Improve the inventory policy for spares, thereby improving the availability of and providing for quick replenishment of failed parts

A combination of both strategies can be seen in commercial practices today. This section discusses the application of successful commercial transportation and logistic practices and their potential application for the military, specifically for the MIME inventory model of repairable weapon components.

In commercial practice, the exchange of damaged parts for repaired parts is called reverse logistics. Banks (2002) defined reverse logistics as "the timely and accurate movement of serviceable and unserviceable materiel from a user back through the supply pipeline to the appropriate activity." For our research, the "materiel" is failed components of a weapon, and the "activity" is the repair process.

The end goal of the Air Force's repairable parts inventory system is to maximize the mission capability of the weapons the system it's servicing. As stated previously, the only way to improve MC is to improve either the reliability of the weapon (increase MTBM) or the repair or replacement cycle time (decrease the MDT). The focus of this literature review is on examining methods for decreasing MDT. If spare parts are available, MDT is the time it takes to order, receive and install the spare part. If spare parts are not available, MDT is the time it takes for the part to be ordered, shipped, received and installed.

2.1 Metrics Used in Industry

Banks (2002) claims the two most important metrics of a reverse logistics system are the requisition wait time (RWT) and customer wait time (CWT). RWT is the time required to make an order. CWT is defined as the time from when an order is placed until the order is received. Sometimes order ship time (OST) substitutes for CWT, due to the fact that OST is the same as CWT when there are no backorders. The Equipment Downtime Analyzer (EDA) developed by RAND® as part of their VM initiative presents a hierarchy of metrics (Dumond, *et al.* 2001).

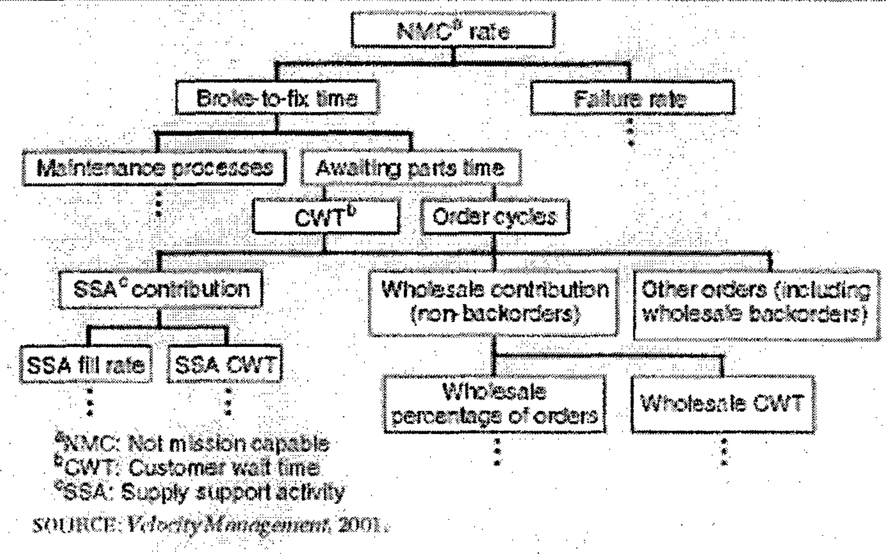

Figure 2.1: Hierarchy of Metrics

The hierarchy in *Figure 2.1* systematically breaks down MC into its components' MTBM (that is, the right branch) and MDT (specifically, the left branch, which is our focus). Here, NMC represents the non-mission capable rate, the complement of MC, defined as:

$$NMC = 1 - MC = \frac{downtime}{uptime + downtime} = \frac{MDT}{MTBM + MDT}$$
$$= \frac{\text{Average Repair Time}}{\text{Failure Cycle Time}} = \text{Average Repair Time} * \text{Failure Rate}$$

Equation 2.1

MDT is further broken down into the repair process and the replacement process. As shown in *Figure 2.1*, the replacement process is further divided to determine the contribution from each segment of the supply chain. As defined by Dumond *et al.* (2001), CWT has three components:

- Order time, or the how long it takes to place an order
- Backorder time, or how long before the requested item is available
- Shipping time, or how long it takes to ship the item to the customer

In a simple simulation, Kang *et al.* (1998) showed that reducing component process times of the repair process has a greater effect on improving MC than does improving the spares inventory. In a more complex simulation using a Dyna-METRIC model for the C-5, Ramey (1999) similarly showed that reducing the pipeline time was more effective than relying on a large inventory of spare parts over several scenarios. But of course, a reduction in pipeline time has a direct effect on inventory levels. By Little's Law, a decrease in cycle time results in a proportional decrease in pipeline inventory for some fixed throughput (Nahmias 2001). In 1990, a one-day reduction in the Air Force pipeline would have resulted in a $16M - $25M savings in inventory costs (Condon *et al.* 1999); however, a shorter and more reliable CWT also means faster replenishment of spare parts inventory. If CWT is short enough, it could result in reducing inventory levels to the point where buffer stock was required only to guard against potential delays and low replenishment reliability (Dumond *et al.* 2001).

Spare parts inventory positioning can have significant effect on reducing repair cycle times. Dumond *et al.* (2001) suggest metrics for measuring inventory effectiveness. They present two types of metrics: performance metrics and resource metrics. The performance metrics include:

- Equipment readiness or MC
- CWT, one of the most important factors affecting MC
- Fill rate, the percentage of customer requests that are filled immediately from inventory point
- Accommodation rate, the percentage of requisitions for items that are regularly stocked (a measure of inventory breadth), whether or not that item is stocked at the time of request

The resource metrics include:

- Inventory investment, the dollar value of the required objective, or the maximum amount of an item that a supply clerk will order up to for that site when replenishing inventory levels (dollars)
- Transition costs, the up-front investments to increase inventory levels of existing items or to add new items (dollars)
- Workload, the level of activity required to fill customer orders and maintain inventory at the proper levels (percent time)

Gue (1999) argues that two commonly used warehouse metrics, average days delayed and average cycle time, do not necessarily reflect customer service and CWT. Customers do not care how efficiently a warehouse operates; they want their parts as quickly as possible. The customer does not see a benefit if the warehouse can reduce its cycle time by one hour, unless the order ships earlier. Since both private carriers and scheduled truck deliveries operate on specific schedules, and pick up outgoing shipments at a certain time, Gue (1999) introduces a new customer-focused metric: the percent making cut-off (PCO). PCO accurately gauges how many orders made by a certain "cut-off" time are shipped the same day, thereby improving CWT and customer service. To achieve a better PCO, Condon *et al.* (1999) recommend better coordination between warehouses and shippers. This has been implemented with great success under the Army's VM initiative (Wang and Champy, 2000), which is discussed later in this report.

When using CWT as a metric, it is important to know the mean, median, 75th percentile, and 95th percentile of the CWT to gain a sense of process variability (Dumond, *et al.* 2001, Wang and Champy 2000). The authors argue that reducing CWT variability is almost as important as reducing the mean for the following reasons (Dumond, *et al.* 2001):

- Mechanics will only wait so long for a spare part before they begin placing duplicate orders or hording parts
- Because repair jobs typically require multiple parts, process variability makes it difficult for maintainers to repair equipment in a timely fashion

To reduce variability, Dumond *et al.* (2001) examined each shipment at the 95th percentile or above to see where the process had failed. They also recommended the use of scheduled deliveries of dedicated trucks as a method for reducing variability.

2.2 Crossdocking

There are four major functions of a warehouse: receiving, storage, order-picking and shipping. Crossdocking is defined as a logistics technique that eliminates the storage and order-picking functions of a warehouse while still allowing it to serve its receiving and shipping functions. Shipments are transferred directly from incoming to outgoing trailers without intermediate storage (Gue 2001). For our research, crossdocking may be a way to consolidate scheduled LTL deliveries; however, the primary benefit would be cost, a resource metric, and not time, a performance metric. Gue (2001) claims that a product is a good candidate for crossdocking when its demand meets two criteria: low variance and high volume. These criteria seemingly rule out crossdocking as a viable option for our repairable parts system, because the failure of parts is often unpredictable and the volume is typically low (Wang and Champy 2000).

2.3 Using Private Express Commercial Carriers

Using private commercial carriers to handle all shipping operations is a common commercial practice due to the economies of scale provided by carriers such as FedEx®, United States Postal Service® (USPS®), and United Parcel Service® (UPS®). Condon *et al.* (1999) compared FedEx®, a commercial carrier, to the Air Force's Air Mobility Command (AMC). The authors found that the mean time in the pipeline for FedEx® was 3.5 days shorter than for AMC for parts under 150 pounds traveling from CONUS (Continental United States) to Spangdahlem, Germany.

Ramey (1999) simulates the usage of commercial carriers versus the current transportation method of shipping spare parts for a traveling C-5 cargo aircraft. Ramey compares a High Velocity Infrastructure (HVI) to the Air Force's current logistics infrastructure. HVI is defined as a logistics infrastructure in which speed of processing is deliberately favored over mass of inventory. The HVI used for Ramay's (1999) simulation assumes:

- Next-day deliveries of all forward and retrograde depot-level repairables within CONUS are available via commercial carriers
- Two-day deliveries of repairables to all overseas locations are available via commercial carriers
- Wholesale (depot) repair flow times are approximately the same as the hands-on repair time for each part (that is, no queue at the repair facility)

Under baseline conditions, the HVI scenario's MC is roughly equal to that of the current logistics scenario, but with only one-sixth of the inventory and one-third of inventory value (inventory levels are computed as a direct function of pipeline times). The author also shows that HVI is better at handling variability in demand rates and spares acquisition lead times. Ramey (1999) points out that one aforementioned warehouse metric, fill rate, is inappropriate in an HVI because HVI relies on speed rather than inventory holdings.

Dumond (2001) and Wang and Champy (2000), in their discussions of VM, advise against using commercial carriers. They found that in the past, the Army tried to find the "optimal" shipping method for each item, based upon its size, weight and urgency. Small packages were sent by a premium air service (FedEx®), while larger packages were sent by surface carriers (UPS®), with large shipments justifying entire dedicated truckloads and smaller shipments using LTL (Wang and Champy 2000; Dumond 2001). This "optimal" mix introduces variability into the processing and transit times. They propose that using scheduled deliveries from a fleet of dedicated trucks could achieve the same speed with the same (or fewer) costs and greater reliability.

2.4 Using Scheduled Deliveries

Many authors argue that using commercial carriers for some shipping operations only increases the variability and uncertainty of the process. The process to move individual packages may not work as efficiently at higher volumes. Wang and Champy (2000) point out that high-volume commercial operations like Wal-Mart® and McDonald's® do not supply their retail stores with FedEx® or UPS® deliveries, but with scheduled deliveries from a dedicated truck fleet. Just because FedEx® can ship one package overnight to a single customer does not mean that FedEx® is the most efficient way of shipping a larger quantity of material; however, using scheduled deliveries may result in supply trucks leaving depots half empty. To reduce this occurrence, Wang and Champy (2000) suggest better positioning of inventory. They also emphasize that a partially full truck should not be seen as under-utilization, but as an asset during times of increased demand. Finally, they claim that long-term contracts for daily scheduled truck service are cheaper than aggregated package-by-package charges.

Because many of the routes between supply depots and bases have driving times of two days or less, scheduled deliveries from a fleet of dedicated trucks could achieve transportation times matching the performance of FedEx®. The proponents of VM argue that deliveries on routes that could be scheduled every day or every other day would address the issues both of speed and of reliability. Furthermore, receiving operations could be simplified because all shipments would be received at once, rather than receiving a stream of unsorted, unscheduled packages from multiple sources (Dumond 2001, p. 25; Wang and Champy 2000).

VM has had such success with the use of scheduled deliveries that even items that are eligible for air shipments or bulk considerations are now sent on scheduled trucks. Scheduled deliveries have allowed bases to reduce their inventory and inventory costs and to rely more heavily on the depot for spare parts because of speed and reliability. Furthermore, if the trucks are not already full, shipping from the base and depot results in no additional transportation costs. Of course, more frequently scheduled deliveries mean shorter CWT. Since the implementation of VM, CWT for all active Army units has improved 56-59% in terms of the median, the 75th, and the 95th percentiles (Dumond 2001). The pilot implementation of VM at Fort Bragg has improved CWT metrics 72-80% (Wang and Champy 2000). VM is currently working on extending the scheduled deliveries concept to OCONUS (Outside Continental United States) facilities.

2.5 Direct Shipments

Vehicle routing in a multi-echelon system with multiple bases being supplied by a single depot can be handled in two ways:

- Vehicles run a route servicing one base per trip (direct shipments)
- Vehicles run planned routes servicing many bases in a single trip

Under direct shipments, the type of routing used is a function of the shipment and vehicle size. Gallego and Simchi-Levi (1990) illustrate this principle. They look at a situation where there is one warehouse serving a number of retailers spread over a geographically disperse region. Demand is retailer-specific and inventory holding costs are only incurred at the retailer. A fleet of identical finite-capacity vehicles services the retailers. This paper develops a guideline to determine when direct shipping is cost effective. They present results for the system described above that show "direct shipping is at least 94% effective whenever the minimal economic lot size over all retailers is at least 71% of the truck capacity" (Gallego and Simchi-Levi 1990). It is important to note that this is just a guideline; there may be other factors affecting the routing decision.

Multiple papers use direct shipping as a means of satisfying the emergency needs of specific bases. One such example is the model developed by Muckstadt and Thomas (1980). Their model is a variation of Sherbrooke's (1986) Vari-METRIC model, which has the added direct-shipping option in the case that a base should run out of an inventory item. The cost effectiveness of this model was investigated in a paper that will be discussed below in the section on lateral transshipment.

2.6 Lateral Transshipments

In the multi-echelon shipping model, lateral transshipments have been proposed in the literature as another means of expediting shipping times. Lateral transshipments are defined as "movement of stock between locations at the same echelon level" (Herer and Tzur 2001). Lateral transshipments have emerged in the literature in many different forms. To gain an understanding of how lateral transshipments can be used, a few of the models involving lateral transshipment are discussed below.

Lee (1987) introduced a model that incorporated lateral transshipments into the multi-echelon inventory system. The author separates bases at the lowest echelon into pools according to geographical region. Lateral transshipments are handled separately within each pool, and no shipments can be made outside the pool. The base from which the transshipment is to come is randomly selected from within the pool. Lee's model assumes that all the bases, including shipping times from the depot, are identical. Drawing from the last assumption, it is logical to assume that the shipping time from base to base must be less than the shipping time from depot to base. Another limitation is that transshipments are only used in the emergency case in which a base runs out of available inventory. Due to these assumptions, the main focus of Lee's paper is modeling the expected number of backorders in the system. Lee uses the expected number of backorders as a driver to determine the batch size for lateral transshipments and for determining the optimum stocking levels within the system.

Axsäter (1990) considers the model developed by Lee (1987), but relaxes the assumption that all bases are identical. Axsäter focuses on modeling the demand at each base correctly. Demand in the lateral transshipment model is a function of the inventory situation at the base. Simply put, with positive inventory on hand, the base faces both normal demand and demand from other bases within its pool (lateral transshipments), whereas with no positive inventory on hand, normal demand is backordered.

Grahovac and Chakravarty (2001) take Axsäter's (1990) model and extend it to allow lateral transshipments to be made when a specified inventory level is reached. Prior to this, transshipment occurred only when a base ran out of available inventory. There is another fundamental difference between Axsäter's model and that of Grahovac and Chakravarty. In Axsäter's model, items are laterally transshipped within the group before they are sought from the depot, while in Grahovac and Chakravarty's model, the depot is always queried first. Grahovac and Chakravarty make the inference that this fundamental difference makes the model more appropriate for the commercial setting where retailers are more likely to be independent, while Axsäter's model is more appropriate in the military setting where bases are interdependent and information is shared. In reading about military supply chain practices, it was discovered that Grahovac and Chakravarty's inference may not be completely accurate, as bases in the military model resemble those in the commercial sector more than Grahovac and Chakravarty assumed.

In the discussion of how to manage lateral transshipments, this paper brings two important guidelines of lateral transshipment to light:

- Take advantage of the information about remaining lead times for outstanding orders in deciding whether to place emergency orders
- Consider the current inventory levels in choosing the retailer from which to source the transshipment

Increased system performance can be expected if the "relative information is used in decision making" (Grahovac and Chakravarty 2001). The authors also make the observation that for this increased system performance to be realized, the supply chain decisions must be centralized; supply chain decentralization only muddies the water.

Up to this point, the literature has viewed lateral transshipments as a tool to satisfy an emergency lack of inventory. Herer and Tzur (2001) developed a model in which lateral transshipments are used as a normal means of inventory replenishment. In this setting, transshipments become a means of avoiding costs associated with specific retailers' high replenishment costs, shipping costs, and holding costs. In other words, transshipments allow the firm to determine the most cost-effective locations within the supply chain where central inventory is to be held, as opposed to each retailer independently holding its own inventory. In this system, each node within the supply chain has three potential sources of replenishment: direct shipment from the outlet, transshipments from other nodes within the same echelon, or carry-over inventory from the previous time period. In each time period, the node is replenished by one and only one of these sources. Also, transshipments are never made in both directions between two locations. Using transshipments in this manner could help a firm fully realize additional cost savings.

2.7 Combination of Lateral Transshipments and Direct Shipments

Alfredsson and Verrijdt (1999) developed a model that incorporates both lateral transshipments and direct shipments to satisfy emergency needs at the base level. They created a hierarchical structure for filling demand:

- Fill demand from stock on hand
- Fill demand through emergency lateral transshipment (ELT)
- Fill demand through direct shipment from the warehouse
- Fill demand through direct shipment from the plant

In this structure, lateral transshipments come from bases on the same echelon level, the warehouse is considered to be one echelon higher than the base, and the plant is considered to be one echelon level higher than the depot. Transshipments are handled in the same manner as in the model developed by Axsäter (1990), although Alfredsson and Verrijdt's (1999) model only looks at one pooling group. Direct shipments are handled in the same manner as the model developed by Muckstadt and Thomas (1980). Alfredsson and Verrijdt's (1999) model is also limited to the two-echelon situation. They construct a costing structure that allows them to compare and contrast their model with other similar models. They compare their model with Axsäter (1990), Muckstadt and Thomas (1980), and Graves (1985). Axsäter's model only incorporates lateral transshipments, while Muckstadt and Thomas' model only incorporates direct shipments. The model created by Graves (1985) is an extension of Sherbrooke's (1986) Vari-METRIC model, and does not include any emergency supply flexibility. Graves' (1985) model serves as the baseline in this comparison. Each of the models' results is resolved to a percent cost improvement over the baseline model. The combination of lateral transshipments and direct shipments that Alfredsson and Verrijdt developed realizes the most impressive cost savings over Graves' model, ranging anywhere from 2%-30%. "From this we can conclude that supply flexibility always pays off" (Alfredsson and Verrijdt 1999).

2.8 Scheduling Priorities at the Repair Facility

One method of improving repair cycle time is improving the scheduling rules of parts waiting for repair at the base or depot. METRIC assumes the repair facility has infinite capacity, but this is not always the case. Parts must often wait in queue for a repair resource. Hausman and Scudder (1982) compared many different scheduling rules for a multi-indenture MOD-METRIC-type system with a limited capacity repair facility using simulation. In their study, they found a scheduling rule that selects a job of the component type that is required by the largest number of weapons awaiting parts for assembly combined with a shortest processing time (SPT) tiebreaker to be the best rule. This rule is termed MSTREQ in this paper. This rule resulted in a 36% decrease (from 6.46 to 4.13) in the mean days delayed of a part undergoing repair when compared to simple FIFO scheduling.

Scudder (1984) shows that the MSTREQ scheduling rule is again the best rule in a multiple failures scenario. Building off Hausman and Scudder (1982), Scudder (1984) compares scheduling rules at the repair shop in the case of multiple failures (that is, dropping Sherbrooke's [1968] and Muckstadt's [1973] assumption that a failed weapon is the result of *only one* failed LRU and that failed LRU is the result of *only one* failed SRU). Assigning scheduling priorities under this multiple failure scenario is more complicated because the repair of a weapon cannot begin until *all* required parts are available. Under the multiple failures scenario, the MSTREQ rule results in a 39% decrease in mean days delayed (from 13.03 to 8.01) when compared to FIFO scheduling.

Guide *et al.* (2000) consider scheduling rules for a repair shop with no spares inventory, claiming this is a more accurate representation of where military logistics systems are heading. They criticize Hausman and Scudder (1982) and Scudder (1984) for using dynamic scheduling rules. Rules updating a job's priority at each operation are based upon the job's progress through the shop (for example, MSTREQ), which work well in combination with spares stocking and with low-variability environments. Guide *et al.* (2000) cite

Guide *et al.* (1997a, b, c) in claiming that dynamic scheduling rules perform poorly in repair shops with high amounts of uncertainty. They further claim that work by Lawrence and Sewell (1997) shows that simpler, static scheduling rules (for example, FIFO, SPT, and Earliest Due Date [EDD]) outperform complex optimization scheduling systems in shops with moderate to high levels of uncertainty. Given this evidence, they compare these simpler rules in a simulated repair shop servicing multiple product structures. Under several scenarios, they show that SPT minimizes the mean flow time of jobs through the repair shop. For our simulation, the use of these scheduling rules can be a method of reducing the cycle times of failed parts.

2.9 Cannibalization

Cannibalization is a method of improving or better utilizing inventory positioning. As described by Ormon *et al.* (2003), cannibalization occurs when a failed component in a weapon system is replaced with a functioning component from another system that is failed for some other reason. Cannibalization occurs because of shortages in spare parts and a desire for short maintenance time. The desire to reduce or eliminate the status of "hangar queens," which is a key reportable metric for maintenance managers, also contributes to the use of cannibalization. Cannibalization actions can take at least twice as much time to perform as regular repair actions, forcing maintenance crews to work overtime. The prevalence of cannibalization in the Navy and Air Force is demonstrated by roughly 850,000 cannibalization instances between 1996 and 2000 (Ormon *et al.* 2003). For our simulation, cannibalization is viewed as an internal function of base operations, having little affect on the generation of part orders or shipments. Cannibalization, however, is an important attribute of the Air Force's repair and replenishment activities, and therefore, warranted reviewing.

3 Literature Review of Part Failures

The failure of aircraft parts is the catalyst for the entire system. A statistical distribution must be assigned to the event of a failure in order to model it. Part failure is a complicated event, and research has revealed that it is approached in many different ways. This section analyzes the different approaches and brings forth the advantages and disadvantages of each distribution. Before getting into the distributions, we will provide a short introduction to part failure.

Miller and Abell (1992) assume there are only two levels of indenture: LRUs and SRUs. The LRU is the parent part to the SRU. In effect, the LRU/SRU relationship resembles that of the aircraft/LRU relationship. SRU failures are independent primary events. Thus, the number of repairable LRUs that fail at the base depends upon the number of SRU failures. Each LRU and SRU has its own TTF. When all parts are functioning, an aircraft has an "up" status. In the event that one or more TTFs are less than equal to zero, the aircraft status immediately switches to "down." The aircraft cannot be returned to the "up" status until a new part is placed in it (Patten 1999). The uncertainties in this failure process require careful modeling attention. Hill *et al.* (2001) create a neural network that determines at what value a part can be classified as operating in a healthy state as opposed to being classified as failing. The neural network is used to build two distributions. The first distribution models the uncertainties in the time a failure is predicted. The second distribution models the prediction of a failure for a healthy component (false positive). This is an interesting idea that introduces a false alarm rate.

The failure of aircraft parts can be random; however, the parts do have a service life. This indicates that they will follow a wear-out cycle. *Figure 3.1* shows a graphical representation of the life of a wear-out part. The failure rate is denoted by m(t). As shown, m(t) changes over time. The dashed lines are estimations of failure rates over different time intervals.

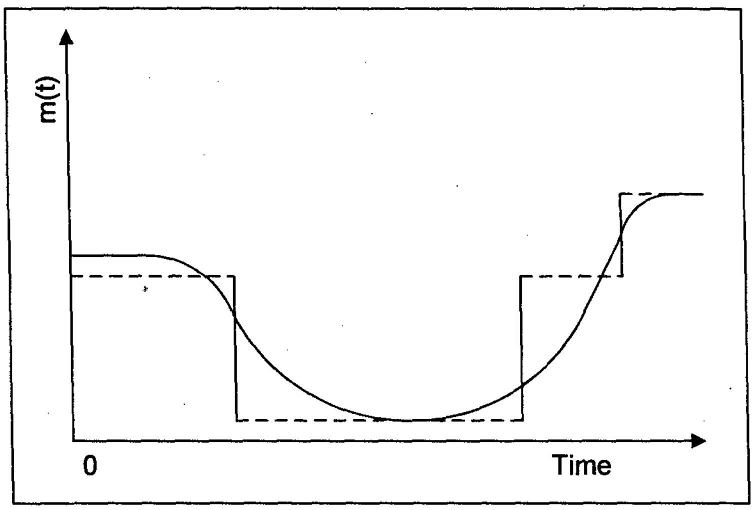

Figure 3.1: Bathtub Curve Representation of Constant Wear-Out*

* Source: Sherbrooke 1992

3.1 Exponential Distribution

There are two types of failure rates: constant failure rates and failure rates that vary with time. A constant failure rate can be related to the exponential distributions of TTF over each time interval. This exponential distribution possesses a unique characteristic called the lack of memory property. The distribution is often used in reliability studies to model time to failures (Montgomery, Runger 1999). The only drawback is that failures cannot vary with time. They are constant and do not change. This is a more simplistic approach to modeling failures. The probability density function for a random variable X that equals the distance between counts of a Poisson process with a mean $\lambda > 0$ is

$$x = 0 \qquad f(x) = \lambda e^{-\lambda x}$$

Equation 3.1

3.2 Exponential Distribution with Varying Failure Rates

Sherbrooke (1992) provides further analysis for failure rates that vary with time. Here, it is assumed that the failure rate cannot be predicted. Instead, empirically derived formulas are used to estimate a probability distribution for the number of demands during a time period. Below is the relationship between the failure rate and an arbitrary probability distribution for the time to failure.

$$t=0 \quad m(t) = \frac{h(t)}{[1-H(t)]}$$

Equation 3.2

where

m(t) is the failure rate,

h(t) is an arbitrary probability distribution for TTF,

and H(t) is the cumulative distribution function.

To determine the number of demands in a fixed period of time, a probability distribution is required. Constant failure rates produce an exponential distribution for TTF and a Poisson distribution for the number of demands in any fixed period of time.

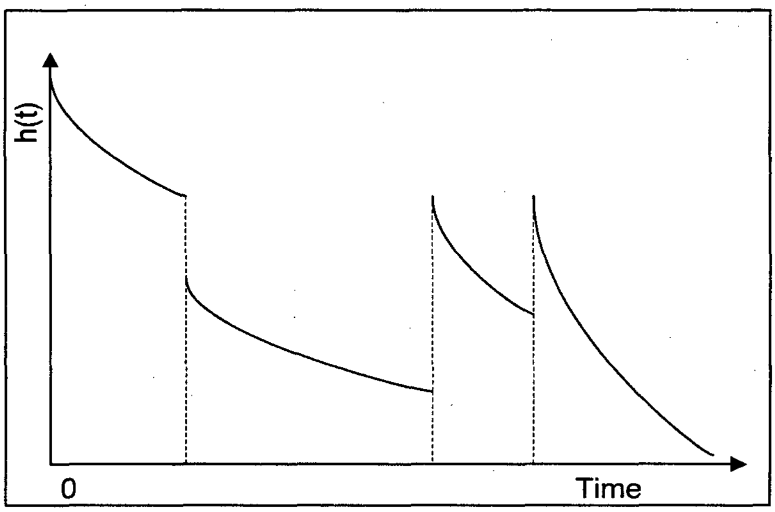

Figure 3.2: Failure Rate Varying with Time*

* Source: Sherbrooke 1992

As shown in *Figure 3.2*, there are discontinuities at each change in failure rate. Each dotted line represents a new time interval. This approach allows for varying failure rates. This can be considered more realistic than an exponential distribution.

3.3 Negative Binomial Distribution

The negative binomial distribution allows the variance to exceed the mean. Because demand for spare parts can be more erratic than a Poisson process, one might consider the negative binomial approach (Slay *et al.* 1996). Sherbrooke (1992) focuses his interest not on the time to next failure, but on the mean and variance-to-mean ratio for the number of failures over time. Miller and Abell (1992) also use this distribution to account for part failure. The negative binomial distribution has two parameters, which can be set as functions of the specified mean and variance-to-mean ratio (VTMR). The formula they use for the VTMR is:

$$VTMR = 1.0 + 0.14 Mean^{0.5}$$

Equation 3.3

After the VTMR and desired mean are obtained, the parameters p and r can be solved for, using the following formulas:

$$p = \frac{1}{VTMR} \quad \text{VTMR} > 1$$

Equation 3.4

$$r = \frac{Mean}{VTMR - 1} \quad \text{VTMR} > 1$$

Equation 3.5

This method has some problems in that it is difficult to choose a suitable VTMR. This estimator has poor sampling properties and is unstable over time. The negative binomial, however, is a widely used distribution when considering part failures.

3.4 Binomial Distribution

Wear-out items generally have a variance that is less than the mean. For this matter, the binomial distribution can be used to model failures. To use this distribution, the average number of failures and probability that a single aircraft will fail must be known (Culosi 2001). The probability of a failure is always constant.

$$f(x) = \binom{n}{x} p^x (1-p)^{n-x} \quad \mathrm{x} = 0,1,\ldots,\mathrm{n}$$

Equation 3.6

where

n = the number of trials,

x = the number of failures,

and p = the constant probability of failure.

Also,

$$E[x] = np$$

Equation 3.7

$$V[x] = np(1-p)$$

Equation 3.8

3.5 Weibull Distribution

For wear-out items, the probability distribution of time to next failure does not decrease uniformly like the exponential (Sherbrooke 1992). Instead, a peak value occurs to the right of the origin. This represents distributions such as Weibull, gamma, and log normal. The Weibull distribution is a two-parameter generalization of the exponential. The parameters of Weibull provide a great deal of flexibility to model systems in which the number of failures increases with time. Wear-out items exhibit this quality; therefore, many reliability engineers prefer using this distribution. Parameters a and b are greater than zero.

$$f(x) = ab^{-a} x^{-a-1} e^{(-x/b)} \quad \mathrm{x} > 0$$

Equation 3.9

The disadvantage lies in calculating the distribution parameters. Doing this requires solving two nonlinear equations; however, when the TTF needs to be drawn probabilistically, the Weibull is preferable because it is easier to sample than other distributions.

3.6 Gamma Distribution

Sherbrooke (1992) prefers using the gamma distribution over Weibull, because one can specify a mean and variance-to-mean ratio and calculate the parameters of the gamma distribution directly. Those approaches mentioned before *Section 3.6* assume that a part and its replacement will not fail in the same cycle. As cycles are extended in length, the chance of this happening steadily increases. There can be two failures of the same part type during the same resupply cycle. For this situation, the Weibull and gamma distributions are two analytic approaches that best account for multiple failures at one location. One advantage that the gamma distribution possesses over Weibull is the ease of calculating parameters, as mentioned previously. Another advantage is that the probability distribution for the number of demands can be computed analytically. This is especially beneficial when the failure rate is estimated by the horizontal line segments shown in *Figure 3.2*. The mean and variance of this probability distribution can easily fit the gamma distribution. The disadvantage of using the gamma distribution surfaces when estimating some other probability distributions of TTF. This is because gamma is a unimodal distribution. Sherbrooke (1992) suggests using a mixture of an exponential and gamma distribution, creating a bimodal distribution; however, this works against the analytic calculation of the probability distributions. He describes a computer simulation that takes failure estimates based upon both random failure and wear-out. The simulation draws the random TTF from an exponential probability distribution and draws the next wear-out failure from a wear-out distribution. The wear-out distribution can be any of the above-mentioned distributions, excluding exponential. The smaller time of the two distributions is taken as the next failure. The simulation also probabilistically determines whether the failed part can be repaired or must be condemned.

3.7 Non-Stationary Poisson

Slay *et al.* (1996) talk about indicators for spare-part demand. They mention that sorties-per-day is a better indicator than flying hours. Sherbrooke (1996) compares these two indicators in detail. For steady-state conditions (constant sortie lengths), Slay *et al.* recommend the negative binomial distribution. This is not entirely accurate, as situations in the Air Force may cause variation in the demand process. This can be caused by wartime, when the length of sorties changes quickly each day. For steady-state conditions in which the demand is constant, stationary Poisson processes can be used to approximate demand. For dynamic conditions, a non-stationary Poisson process can approximate demand. In this case, the probability of a given number of demands in a time interval depends upon both the length and the location of the time interval (Slay 1996).

4 Modeling Approaches

The system, which has been described up to this point, encompasses a very complicated and intricate set of interactions and processes. As seen in the literature review, there have been many mathematical models developed for the MIME system; however, these mathematical models fall somewhat short in capturing the complexity of this system. All the models must make limiting assumptions that degrade the amount of variability in the system. In this research, simulation was used to allow the development of a model that is more complete, flexible, and expandable.

4.1 Baseline Model

A baseline model was developed in Arena® 7.0 to simulate the current MIME supply chain for the weapon system being studied. This baseline model will be compared to various commercial logistic practices that potentially could be adopted by the Air Force to improve supply chain efficiencies.

It was important to the accuracy of our results that our model be a close representation of the current repairable parts supply chain system. Throughout the modeling process, we communicated with our contacts at the Air Force. We both received process data from them as well as provided them with validation statistics and model data. This open line of communication allowed us to gain a full understanding of the system we were modeling. *Appendix 1* contains a list of all model inputs along with their distributions and parameters. The data provided in *Appendix 1* was developed in coordination with the Air Force and verified through our contacts.

4.1.1 Supply Chain Structure

In the baseline model, there are six independent bases supported by a single depot. There are 24 aircraft assigned to each unit, three units assigned to each squadron, and one squadron assigned to each base. In this structure, there are a total of 72 aircraft assigned to each base. This results in a total of 432 aircraft within the system. The six bases are split into two regions, with three bases in each region. *Figure 4.1* details the structure for the baseline model. In the figure, we have illustrated the squadron, unit, and aircraft for Base 3. The other bases have a similar structure.

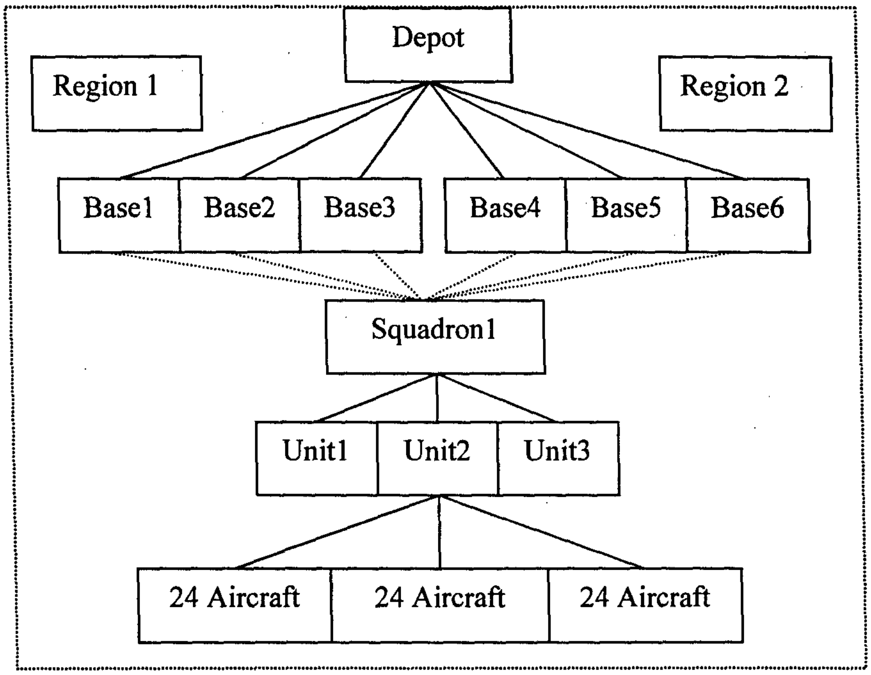

Figure 4.1: Supply Chain Structure

4.1.2 Weapon Systems and Bases

The baseline model represents weapon systems (for the purposes of this research, an aircraft) as objects with two levels of indenture. Initially, each aircraft is assigned a base number, index number, and tail number. The index number is a model-wide unique number assigned to each aircraft. This number allows the user to compare aircraft individually across bases. The tail number is unique to each aircraft at a given base. The base number indicates the base at which the aircraft is stationed. The model can accommodate a variable number of bases, and each base can have a variable number of aircraft (both values are set by the user). *Table 4.1* displays the relationship between these three identification numbers.

Table 4.1: Identification of Aircraft

Index Number	Tail Number	Base Number
1	1	1
2	2	1
3	3	1
4	1	2
5	2	2
6	3	2
7	1	3
8	2	3
9	3	3

In *Table 4.1*, the user has set the model to simulate a MIME system comprised of three bases, with aircraft stationed at each base. Note that each aircraft has a unique index number, but aircraft from different bases may be assigned the same tail number. For example, there are three tail number 2 aircraft, one at each base. Currently, the baseline model contains six bases with three units of 24 aircraft each assigned to each base. As stated previously, this yields a total of 432 aircraft existing in the Air Force (AF) supply chain represented by the baseline model.

Each weapon system has two levels of indentures. The first level of indenture entails aircraft that are made up of multiple LRUs. These LRUs are in turn comprised of multiple SRUs constituting the second level of indenture. The number of SRUs per LRU type can vary as set by the user; however, the number of LRUs per aircraft remains constant system-wide. In the baseline model, there are six individual LRU types. Each of the 432 aircraft in the system is comprised of six LRUs, one of each type. LRUs of the same type are identical and interchangeable. *Table 4.2* illustrates the first level of indenture in the baseline model.

Table 4.2: LRU Association

Index Number	Tail Number	Base Number	LRU Type
1	1	1	LRU 1
			LRU 2
			LRU 3
			LRU 4
			LRU 5
			LRU 6
2	2	1	LRU 1
			LRU 2
			LRU 3
			LRU 4
			LRU 5
			LRU 6
3	3	3	LRU 1
			LRU 2
			LRU 3
			LRU 4
			LRU 5
			LRU 6

As previously stated, the number of SRUs per LRU can vary per LRU type and is set by the user. *Table 4.3* illustrates this for the LRUs of the aircraft with index number = 1. In *Table 4.3*, the user has set the number of component SRUs for LRU types 1 through 6 to equal four. For the aircraft represented in *Table 4.3*, and for all aircraft in this instance of the model, there are 24 distinct SRU types. SRUs are identified by two numbers: the first number identifies the LRU it belongs to, while the second number identifies the type of SRU for the associated LRU. The SRU types for each LRU type are unique and cannot be shared between LRU types. But within the same LRU type, the component SRUs are identical. For example, the four SRUs comprising LRU type 1 of aircraft index number 1 are identical to the four SRUs comprising LRU type 1 of any other aircraft in the system. In the baseline model, each of the six LRU types is comprised of four SRUs yielding a total of 24 SRUs per aircraft.

Table 4.3: SRU Association

Index Number	LRU Type	SRU Type (LRU, SRU)
1	LRU 1	SRU (1,1)
		SRU (1,2)
		SRU (1,3)
		SRU (1,4)
	LRU 2	SRU (2,1)
		SRU (2,2)
		SRU (2,3)
		SRU (2,4)
	LRU 3	SRU (3,1)
		SRU (3,2)
		SRU (3,3)
		SRU (3,4)
	LRU 4	SRU (4,1)
		SRU (4,2)
		SRU (4,3)
		SRU (4,4)
	LRU 5	SRU (5,1)
		SRU (5,2)
		SRU (5,3)
		SRU (5,4)

Index Number	LRU Type	SRU Type (LRU, SRU)
	LRU 6	SRU (6,1)
		SRU (6,2)
		SRU (6,3)
		SRU (6,4)

4.1.3 Weapon Status

In our model, as stated earlier, the weapon system we are dealing with is an aircraft. For the purposes of this model, aircraft are always categorized as being in one of three states:

- Mission-Capable (MC)—An aircraft is designated MC when it is capable of flying a sortie. This status can correspond to an aircraft currently flying a sortie or waiting to be assigned to a sortie.
- Non-Mission-Capable (NMC)—An aircraft is designated NMC when one or more of its critical SRUs fails. This status corresponds to an aircraft that is down either awaiting a spare part or currently in the process of spare-part installation. NMC aircraft cannot fly sorties.
- Phase Inspection (PI)—An aircraft is designated PI when it enters the phase inspection module. While in phase inspection the aircraft is not available to fly sorties; however, the aircraft is not listed as NMC because phase inspection is a scheduled maintenance operation.

The percentage of time each aircraft is in each state is tracked and reported as a key performance metric of the simulation model. In further studies, the number of weapon system states will be expanded to include states such as Partially Mission Capable, Cannibalization, etc.

4.1.4 Failures

The failure of an SRU results in the failure of an LRU and therefore the weapon system. While on the aircraft, SRUs are modeled as entries in a two-dimensional array (*Table 4.4*).

Table 4.4: Time to Failure Matrix

	Base	1						1						1					
	Tail	1						2						3					
SRU Type ↓	**LRU Type →**	LRU 1	LRU 2	LRU 3	LRU 4	LRU 5	LRU 6	LRU 1	LRU 2	LRU 3	LRU 4	LRU 5	LRU 6	LRU 1	LRU 2	LRU 3	LRU 4	LRU 5	LRU 6
(SRU, 1)																			
(SRU, 2)																			
(SRU, 3)																			
(SRU, 4)																			

Table 4.4 is expanded for the first three aircraft at base 1 and will be referred to as the TTF matrix. Each cell of the TTF matrix contains the TTF for the SRU corresponding to that cell. This value is generated by a distribution held in the expression array "mean time to failure" (MTTF). Each cell of the MTTF expression array contains the distribution used to generate the TTF for the SRU corresponding to that cell. Currently, the baseline model contains three levels of MTTF (in hours), each of which is modeled as an exponential distribution with some mean value: high-exponential (500), medium-exponential (400), low-exponential (300). There are eight SRUs assigned to each of these three levels.

While an aircraft is operational, it accrues operating hours, and each cell corresponding to that aircraft in the TTF array (that is to say, every cell representing a component SRU for that aircraft) is decremented equivalently. Aircraft failure occurs when any of the component SRU cells equals or drops below zero.

Before an aircraft can fly a sortie, a pre-flight check is performed to see if all of its component SRUs, and hence all of its component LRUs, are functional. In the construction of the baseline model, pre-flight inspection equates to checking if all of the aircraft's cells in the TTF matrix are greater than zero. If this is not the case, the aircraft's status is set to NMC and the weapon system enters the repair process.

4.1.5 Sortie Assignments

Sorties are generated at the beginning of every day and are assigned to specific bases. The number of sorties assigned to each base is generated from a discrete uniform distribution over the range of 56 and 66 per day. The sorties for each base are divided into two groups (or "runs"), the first scheduled at 8:00 a.m. and the second scheduled at 12:00 p.m. Fifty-five percent of the generated sorties for each day are scheduled for the first run, while the rest are scheduled for the second run. These numbers are intended to simulate approximately 12 planes flying in the first group and 10 planes in the second group, "12 turn 10," for each unit of 24 aircraft as stipulated by Air Force data and personnel. At the scheduled run time, the sorties search for available aircraft. If no aircraft are available at the base when the sortie is scheduled to be flown, the sortie is delayed for a time sampled from a triangular distribution with parameters of 5, 10 and 15 minutes. Following this delay, the sortie again searches for an aircraft. If no available aircraft are found, the process is repeated once more. If an available aircraft is not available on the third attempt, the sortie is aborted; however, if an aircraft becomes available at any point, the sortie is assigned to that aircraft and the aircraft moves on to pre-flight operations. This process of searching for a sortie is a simplified representation of the complex reality sortie assignment process. The multiple searches made for available aircraft along with the delay between searches serves a dual purpose:

- Simulates the window given to a flight crew to initiate their assigned sortie
- Reduces the abort rate to the target level of 5%

The process of sortie generation and assignment is a complicated process that warrants future research and model expansion.

4.1.6 Pre-Flight Operations

Once a sortie has been assigned an aircraft, the aircraft begins flight preparation. The first operations to be performed are refueling and weapons loading. The times required to complete these operations are sampled from triangular distributions with parameters of 8, 10, 12 and 25, 30, 35 minutes, respectively. The aircraft then moves to final preparation, which includes engine start, final systems check, and taxiing. The final preparation time is generated from a triangular distribution of 7, 10 and 12 minutes. Since the aircraft's engines are started during final preparation time, the aircraft's operating hours continue to accrue; therefore, after final preparation is completed, the total elapsed time since engine start is decremented from the TTF values associated with that aircraft.

A pre-flight check of all aircraft component SRUs is then performed. If any of the aircraft's component SRUs have failed, the failed part(s) is/are removed from the aircraft and then sent to the repair process. The aircraft is then forced to wait for spare parts. This is called a ground abort. If no failures are found, the aircraft flies its assigned sortie.

4.1.7 Sortie Flights

Once the aircraft has passed the pre-flight inspection, it is ready for takeoff. The time it takes for each aircraft to take off is generated from the triangular distribution with parameters of 2, 3 and 4 minutes; however, before the aircraft can take off, it must first wait until a base runway is available. After seizing a runway and taking off, the aircraft undergoes an in-flight check. If any SRUs are found to be failed, the sortie is aborted, a runway is seized, the aircraft lands, and then moves to the repair process as previously described. This is termed an air abort. If the aircraft passes the in-flight check, it continues to fly the sortie.

The sortie duration is generated from a triangular distribution with parameters of .5, 1.35 and 2 hours. After completing the sortie, the aircraft identifies a runway and lands. Landing time in minutes is generated from a triangular distribution with parameters of 14, 15 and 16. Once the aircraft has landed, it undergoes its post-flight check. The duration of the sortie is decremented from all the corresponding cells in the aircraft's TTF matrix. If any SRUs are found to be failed, the failed parts are removed from the aircraft and proceed to the repair process, and then the aircraft moves to wait for spare parts. If the aircraft passes the post-flight check, it will continue on to wait for another sortie. Aircraft will continue to fly sorties until one of the flight checks indicates that one or more of its aircrafts SRUs to failure.

4.1.8 Phase Inspections

The total operating hours for each aircraft is tracked. Once an aircraft accrues 280-320 operating hours, it must undergo a phase inspection. While an aircraft is in the phase inspection process, its weapon system stats are set to PI. A PI is a complete check of the aircraft from top to bottom. In our model, when planes leave PI, all aircraft components are assigned a new MTTF, simulating this top-to-bottom schedule maintenance activity. Only two planes at each base can be in PI simultaneously. Aircraft that have accumulated operating hours within this range check the PI process for their base each time after passing the post-flight inspection. If there are already two aircraft in process at PI for that base, the aircraft will continue to fly sorties. Once an aircraft exceeds 320 flight hours, it cannot fly another sortie until completing PI. The PI delay is generated from a triangular distribution with parameters of 7, 10 and 11 days.

4.1.9 The Replacement Process

The model checks each SRU associated with the aircraft sequentially in each flight check. The first time a cell in an aircraft's TTF matrix is less than or equal to zero, the aircraft is considered in failure. When a failed SRU is detected, the aircraft is marked as being failed, and the model removes the SRU from the aircraft. This SRU is sent to the repair process, which is described later. The model then continues to check for other SRU failures on that aircraft. Once a failed aircraft completes the flight check, the model performs an inventory check for the failed parts associated with that aircraft. Inventory levels at the bases and at the depot are modeled using two separate matrices, similar to those shown in *Table 4.5* and *Table 4.6*. These matrices will be referred to as the base inventory matrix and the depot inventory matrix, respectively.

Table 4.5: Inventory at the Base Level

	Base	1			2			3		
SRU Type ↓	**LRU Type →**	LRU 1	LRU 2	LRU 3	LRU 1	LRU 2	LRU 3	LRU 1	LRU 2	LRU 3
(SRU, 1)		3	3	3	3	3	3	3	3	3
(SRU, 2)		3	3	3	3	3	3	3	3	3
(SRU, 3)		3	3	3	3	3	3	3	3	3
(SRU, 4)		3	3	3	3	3	3	3	3	3

Table 4.6: Inventory at the Depot Level

SRU Type ↓	LRU Type →	Depot		
		LRU 1	LRU 2	LRU 3
(SRU, 1)		5	5	5
(SRU, 2)		5	5	5
(SRU, 3)		5	5	5
(SRU, 4)		5	5	5

The number in each cell of *Table 4.5* and *Table 4.6* represents the number of spare parts of a given SRU type that are available at the corresponding location. The user defines the initial value of the cells in these matrices. In the baseline model, there are three of each SRU type held at the bases and five of each SRU type held at the depot. When a failed aircraft initiates an inventory check, the model begins by checking if a spare SRU of the same type is available at the aircraft's base (determined by the aircraft's base number). If a spare SRU of the same type is not available at the aircraft's base, an order is placed to the depot. This order is assigned a backorder status. If a spare part is not available at the depot, the order is held in a queue at the depot with priority given to backorders waiting on a part of that SRU type to be repaired. The aircraft waits in a FIFO queue for the next available spare of correct SRU type to arrive at the corresponding base. When the order is filled at the depot, the part is shipped to the base. Once the part arrives at the base, the inventory level for that SRU type at the base is incremented and a signal is sent to the aircraft queue. This signal indicates that new parts have arrived, initiating an inventory check. When an aircraft finds a needed spare in inventory, installation of that part begins. If there are multiple failures on a given aircraft, the aircraft will wait in queue until all corresponding SRUs are available, but each spare part is installed as it arrives.

Once a needed spare part is available at the base, the installation process begins. At the beginning of the installation process, the aircraft must wait for the part to be issued from supply. This simulates the delay between the time the part arrives at the base and the time the part is ready to be installed on the aircraft, and is generated from a triangular distribution with parameters of 35, 130 and 165 minutes. After the part is issued from supply, it is ready to be installed on the aircraft. Installation times are generated from a triangular distribution with parameters of 60, 84 and 120 minutes. Upon completion of the installation process, the object representing the spare part disappears, and the corresponding cell in the TTF matrix is re-initialized to a number generated by the MTTF expression array. Once all failed parts have been replaced on the aircraft, the aircraft is ready to fly sorties.

4.1.9.1 Repair Process

When an SRU is deemed defective, the model creates an entity representing the defective SRU. It is highly unlikely that this failed SRU can be repaired at the base (Miller 1992). In the baseline model, the probability that a part can be repaired at the base is set to 0.01. In the majority of cases, the SRU must be sent to the depot for repair. If the SRU can be repaired at the base, the travel time to the repair station from local inventory is assumed to be zero and the SRU enters the queue for the base repair resource. If the SRU must be repaired at the depot, the SRU is delayed by some shipping time, and then enters the queue for the depot repair resource. *Table 4.8* details the matrix used to generate the shipping times among different locations in the baseline model. The three different distributions used in the shipping time matrix are outlined in *Table 4.7*.

Table 4.7: Shipping Time Distributions

Number	Distribution (Hours)	Description
1	TRIA(12,81.6,184.8)	This distribution is used to generate shipping times among bases in the same region.
2	TRIA(31.2,170.4,348)	This distribution is used to generate shipping times between the depot and the bases in Region 1.
3	TRIA(76.8, 266.4, 453.6)	This distribution is used to generate shipping times between the depot and the bases in Region 2. This distribution is also used to generate the shipping time among bases not in the same region.

Table 4.8: Shipping Time Matrix

Shipping Time Distribution Matrix in Hours						
	Base 1	Base 2	Base 3	Base 4	Base 5	Base 6
Base 1	0	1	1	3	3	3
Base 2	1	0	1	3	3	3
Base 3	1	1	0	3	3	3
Base 4	3	3	3	0	1	1
Base 5	3	3	3	1	0	1
Base 6	3	3	3	1	1	0
Depot	2	2	2	3	3	3

The repair stations at all bases and the depot give priority to backorders for repair jobs. Repair times at each base and the depot are random distributions set by the user. In the baseline model, the repair times are generated from an exponential distribution with a mean of eight hours.

If the part must be sent to the depot for repair, an order for the part is generated and sent to the depot. This order waits in the order queue at the depot as mentioned earlier. This practice holds with a one-for-one inventory policy. In other words, for every part that is sent to the depot, an order is generated for a part to be sent back to the base, a one-for-one replenishment policy. Again in this queue, backorders are given priority.

Upon completion of the repair process, the SRU becomes functional and the part is sent to inventory. If the SRU was repaired at the base, the base inventory is incremented. If the part was repaired at the depot, the depot inventory is incremented. It is from this depot inventory that the orders are filled. When the depot inventory is incremented, a signal is sent to the queue holding unfilled orders. When this signal is received, all orders are checked. The first order in queue of the same type as the repaired SRU is filled. After an order is filled, the order is shipped back to the base where the order originated. Once the shipment as been received, it is entered into the base's inventory. When a base's inventory is incremented, a signal is sent to the queue holding NMC aircraft. Each aircraft is checked, and the first aircraft in queue needing a part of the same type that was entered into the base's inventory moves to the installation process. If there are no aircraft in need of the SRU, it remains in the base's inventory.

4.2 Shipping

Bases only ship out failed SRUs and receive only functional SRUs. Conversely, the depot only receives failed SRUs and only ships out functional SRUs. Spare and failed parts can be shipped between echelons in two ways: ground shipping and express air shipping. Most parts are shipped on trucks that pick up and drop off parts at the bases and depot; however, MICAP parts are air-shipped, usually arriving at the final destination in one or two days.

4.2.1 Baseline Model with the Use of LTL/TL Shipments

In the baseline model, we can simulate the use of both LTL and TL commercial carriers. These features are controlled through two variables: truck capacity and minimum batch size. The truck capacity dictates the number of SRUs each truck can hold. Minimum batch size is a percentage, which is multiplied by the truck capacity. The resulting number is the smallest number of SRUs that warrant a truck trip.

For example, in the baseline model, the truck capacity is set to 20 SRUs. To turn on the LTL option, the minimum batch size is set to 20%; therefore, a shipping point must have at least four SRUs waiting to be shipped to warrant a truck trip to that location. If that location has less than four SRUs waiting to be shipped, a pick-up is not ordered from the LTL carrier; however, if that location has four or more SRUs waiting, a pick-up is ordered and all parts waiting to be shipped from that location are picked up by the carrier.

To simulate the TL scenario in the baseline model, the minimum batch size is set to 100%. This means 100% of the truck capacity must be waiting at a shipping point before a pick-up is ordered. Currently, a single check of the items waiting to be shipped at each location is made each day at 8:00 a.m. This is true for both the LTL and TL cases.

4.2.2 Baseline Model with Direct Shipments (MICAP)

When parts receive a backorder status, they are shipped with the Model MICAP designation. MICAP shipments are express air shipments. A part can be designated MICAP when the base needs to ship the failed part to the depot or when the depot needs to ship a spare part to a base. The base designates a failed part as MICAP when the base does not have a spare part in its inventory to replace the failed part. The effect is to expedite the shipping of the part from the base to the depot for repair. When the depot receives an order that has a backorder status, it fills the order by shipping the first available part of that type as MICAP back to the base. Parts that receive the MICAP designation wait in a separate queue for air shipping. At 8:00 a.m. each day, a commercial air shipping service picks up all parts needing air shipping and ships them to their respective locations both at the bases and the depot. MICAP shipments are express air shipments with shipping times generated from a triangular distribution with parameters of 22, 24 and 26 hours. The model assumes the air shippers have unlimited capacity. This allows the model to rely upon MICAP if the regular shipping is not able to keep up with the shipping volume, just as the Air Force uses MICAP to expedite shipping.

4.2.3 Baseline Model with Lateral Transshipments

A lateral transshipment (LTS) is defined as a shipment between locations on the same echelon of the model structure, in this case a shipment between bases. For this scenario, the bases are split into regions based upon geographical location. In the baseline model, there are two regions of three bases each. If the LTS feature is turned on, when a failure occurs, the model will first check the base inventory for a spare, then the bases within the region, and finally the depot. The first thing to be done when checking the bases within the same region is to create a list of bases that have inventory available. This list is stored in an array. A selection is made from this array based upon a user-defined criterion. Currently, this criterion is set to choose the base with the most inventory on-hand for that particular part. Once a selection is made, a shipment is initiated from the selected base. If none of the bases in the region have inventory available, the order is sent to the depot. The transshipment scenario assumes the bases within a region are closer to each other than to the depot, and therefore can fill the need in a time-effective manner. The above sections give a complete description of the baseline model. From this model, we developed a set of experiments using commercial shipping practices along with other factors to explore the effect this has on the Air Force supply chain.

5 Experimental Design

A factorial experimental design will be used in our experimental studies. A full factorial design allows for design points to be investigated for all possible factor combinations. The experiments will identify the main effects and the interactions between the factors. In this project, there are 11 factors being studied and each factor has two levels, represented as a 2^k factorial design. Limiting each factor to only two levels provides the minimum number of runs needed to examine all the factors through a factorial design; however, in large experiments such as the one discussed in this report, it becomes computationally difficult to make all the runs necessary for a full factorial design, due to the length of time it takes to run the simulation model; therefore, in our experiments, a fractional factorial design was chosen. In a fractional factorial design, a reduced number of runs can be used to analyze the main effects and interactions between the factors, albeit with less granularity. A 1/16 fractional design was chosen, allowing for 128 runs of the experiment to be made, rather than $2^{11} = 2048$ runs. The experiment is a Resolution V Design. In a Resolution V Design, no main effect or two-factor interaction is confounded with any other main effect or two-factor interaction. *Table 5.1* and *Table 5.2* give a description of the factors chosen. *Table 5.1* lists the factors with a brief description, followed by an explanation of why that factor was chosen. *Table 5.2* lists each of the factor's two experimental levels and the hypothesized effect we expect to see from varying that factor.

Table 5.1: Factors and Descriptions

Factors	Description	Why We Chose This Factor
Commercial Shipping	This determines whether truckload or Less Than Truck Load shipping will be used.	This factor will allow us to experiment using the two major shipping options offered by commercial shipping companies.
Sortie Duration	This factor refers to the actual length of a sortie. The current sortie duration is set at Triangular (.333, 1.747, 2) hours.	Varying the sortie duration will simulate a wartime or training flight schedule, where more operational hours are expected of each plane.
Sortie Frequency	This factor refers to the number of sorties assigned to a base each day. Currently the number of sorties per base is set to ANINT(Uniform(56,67)). This formula generates uniformly distributed integers between 56 and 66.	Varying the sortie frequency also simulates an environment where more operational hours will be accumulated for each plane.

Factors	Description	Why We Chose This Factor
MICAP	This determines whether express air deliveries will be used to expedite backorders.	Allowing MICAP to be turned off creates a situation where more cost effective means of shipment can be explored.
Repair Time	Repair time is the delay time for the repair process. Currently it is set to be Exponential (8) hours.	Varying the repair time will show how sensitive mission capability is to time spent in the repair process.
Inventory Position	In the model, Inventory is set up to be either centralized or decentralized. Centralized indicates that more of the system wide inventory is held at the depot while, decentralized means that more of the inventory is held at the bases.	Many of the other factors are dependent on where inventory is or is not. Changing the inventory position will allow us to explore these relationships.
Time To Failure	This factor refers to the time to failure of individual SRUs. This value is currently generated at three different levels with 8 SRUs corresponding to each level: High-Exponential (500), Medium- Exponential (400), Low-Exponential (300) hours.	Varying this parameter will indicate the sensitivity of the responses to part failure rate.
Pre-/Post-Flight Maintenance	This factor refers to all the maintenance operations that are required to prepare an aircraft for flight and maintenance operations, which are performed after the flight has taken place. The operations currently included in this factor are: Refuel/Weapons Load, Engine Start, Final Systems Check, and Taxiing, Pre-Flight Check, Parking and Recovery, and Service/Debrief.	This factor allows the relationship between the delays for regular maintenance functions and operational availability.
Unscheduled Maintenance	This encompasses all operations associated with the failure of a part. The operations included are: Troubleshooting, Remove Part, Wait for Part to Issue From Supply, Delay for Paperwork, Installation, Operational Check, Operational Check, Signoff Discrepancy, Document Corrective Action	This factor allows the relationship between the delays for unscheduled maintenance functions and operational availability.
Local Repair	This is a percentage that dictates the number of parts that can be repaired at the base level. This is currently set at 1%	Adjusting this percentage will indicate what effect the repair location has on the system.

Factors	Description	Why We Chose This Factor
Lateral Transshipment	This factor indicates whether or not transshipments at the base level can be used as a source of supply.	This factor will allow another shipping option to be added to the three previous options.

Table 5.2: Factors, Levels and Expected Results

Factors	Levels	Expected Results
Commercial Shipping	Truck Load Less than Truck Load	With the truckload option there will be fewer shipments but less responsiveness to change.
Sortie Duration	Low High	Increased sortie duration will result in more operation hours per aircraft yielding more failures.
Sortie Frequency	Low High	Increased sortie frequency will result in more sorties being assigned to each base and in turn more sorties being flown by each aircraft yielding more failures.
MICAP	On Off	Turning the MICAP option off will result in slower response to backorders and longer customer wait times.
Repair Time	Low High	A shorter repair time will increase operational availability by reducing customer wait time.
Inventory Position	Base Depot	This refers to more inventory being held at the bases or a larger consolidated inventory being held at the depot. A larger consolidated inventory will result in a more responsive system.
Time To Failure	Low High	Reduced time to failure results in failures occurring more frequently.
Pre-/Post-Flight Maintenance	Low High	Reducing the time taken to perform maintenance operations before and after a sortie is flown, aircraft will be available to fly more sorties and maintenance resources will be available for additional tasks
Unscheduled Maintenance	Low High	Reducing the time taken to perform the operations surrounding a failure being detected will reduce the pipeline time and therefore the customer wait time.

Factors	Levels	Expected Results
Local Repair	Low High	This refers to the percentage of parts that can be repaired at the base. Increasing the number of parts that can be repaired at the base may result in a more responsive system, increasing operational availability.
Lateral Transshipment	On Off	Allowing each base within a region to be a supply point for the rest of the bases within that region may result in quicker response to backorders increasing operational availability.

Table 5.3 outlines the factor values used in experimentation. Each factor has two factor levels as listed in *Table 5.2*; *Table 5.3* details the actual values corresponding to these levels. The values listed in *Table 5.3* will be important later in understanding the results of our experiments.

Table 5.3: Factors Values

Factor	Low	High
Shipping Option	LTL	TL
Sortie Duration	Triangular (.333, 1.747, 2)	Triangular (.333, 1.747, 2)*1.2
Sortie Frequency	ANINT(Uniform(56,67))	ANINT(Uniform(56,67))*1.2
MICAP	On	Off
Repair Time	Exponential (8)	Exponential (8)*1.2
Inventory Position	Depot	Local
Time to Failure	Exponential (300) Exponential (400) Exponential (400)	Exponential (300)*1.2 Exponential (400)*1.2 Exponential (400)*1.2
Pre-/Post-Flight Operations	The operations currently included in this factor are: Refuel/Weapons Load, Engine Start, Final Systems Check, and Taxiing, Pre-Flight Check, Parking and Recovery, and Service/Debrief.	+20%

Factor	Low	High
Unscheduled Maintenance	The operations included are: Troubleshooting, Remove Part, Wait for Part to Issue From Supply, Delay for Paperwork, Installation, Operational Check, Operational Check, Signoff Discrepancy, Document Corrective Action.	+20%
Local Repair	1% of parts repaired locally	25% of parts repaired locally
Transshipment	On	Off

Each simulation is set up to have a warm-up period, a run length, and a specified number of replications or runs. We used a warm-up period of six months, and then collected data for one year. Our simulation is set to run 128 instances, each of which represents a different combination of factors or design point within the experiment. At the beginning of each instance, the level of each factor is read into the model. The data collected for each instance is written to an Excel worksheet after the run has completed. The simulation is warmed up at the beginning of each instance, and the system is cleared after each run; therefore, the simulation model collects data for 128 independent design points. Each of these 128 design points was replicated five times using a different stream of random numbers, yielding a total of 640 independent observations.

6 Data and Data Analysis

This section will outline the data collected while conducting the previously described experiment along with some analysis of that data. For this experiment, eight different responses were set up to measure the effect the factors had on the model. *Table 6.1* lists all eight of these responses, along with a brief description.

Table 6.1: Responses and Descriptions

Responses	Description
Operational Availability	This is the ratio of time a plane is either available to fly or flying to the time a plane is unavailable due to scheduled maintenance or in phase inspection.
Abort Rate	This is the ratio of sorties aborted to sorties scheduled. Sorties may be aborted due to lack of planes or a failed part in pre-flight or in-flight inspection.
Customer Wait Time	Customer Wait Time refers to the time in hours from when a plane fails and enters unscheduled maintenance until the plane is available to fly again.
Total Transportation Cost	In our model only factors connected to shipping contribute to the total cost. These factors are MICAP, ground shipping, and transshipment. Each factor was assigned a cost per shipment. Data was collected for the number of each type of shipment, and that number was multiplied by the derived cost per shipment to yield the cost of each factor. The Total Transportation Cost is the sum of these three factor costs.
Sorties Flown	This is the cumulative number of sorties flown by an individual aircraft over the course of an experimental run.
Flight Hours	This is the total number of flying hours accrued by an individual aircraft over the course of a replication.
Times Failed	This is the total number of failures incurred by an individual plane over the course of a replication.
Total Backorders	This refers to the total number of backorders that occurred within a replication. A backorder occurs when a part fails and a replacement is not available in the bases inventory.

The first four responses listed in *Table 6.1*, Operational Availability, Abort Rate, Customer Wait Time, and Total Cost. were considered to be the most important metrics for scenario performance. The remaining responses were taken into account while reviewing scenarios to identify outliers and to evaluate the operational validity of the scenarios. Summary statistics were calculated for each of the eight responses to provide insight as to how the data behaves across all scenarios. *Table 6.2* lists each response, followed by the summary statistics for the data collected on each response. The summary statistics included in *Table 6.2* are: n – Sample Size, - Sample Average, $\bar{x}$ - Sample Mean, TrMean – Adjusted Mean, s- Standard Deviation, and s.e. - Standard Error.

Table 6.2: Response Summary Statistics

Response	n	$\bar{x}$	TrMean	s	s.e.
Operational Availability	640	75.2790	75.6610	5.7540	0.2270
Abort Rate	640	0.1378	0.1354	0.08376	0.0033
Customer Wait Time (Hours)	640	70.7830	69.3590	19.7990	0.7830
Total Transportation Cost	640	72,244.0000	69,609.0000	44,770.0000	1,770.0000
Sorties Flown	640	294.2600	293.8900	20.2100	0.8000
Flight Hours	640	413.6600	414.8400	27.3300	1.0800
Times Failed	640	27.0500	27.0400	2.4170	0.0960
Backorders	640	3713.2000	3686.9000	1466.9000	58.0000

Table 6.3 gives statistics that describe the distribution of each response. The symbol $\tilde{x}$ represents the sample median or the "middle" data point in the collected data. The min and max are the minimum and maximum values of the data set. The quartile values, Q_1 and Q_3 in *Table 6.3*, describe how the data is spread around the median. Each data set is divided into four quartiles, each containing a quarter of the data points. The four quartile values are defined as follows:

- min is the minimum value
- Q_1 is the data point one-quarter through the data set
- $\tilde{x}$ is the median
- Q_3 is the data point three-quarters through the data set
- max is the maximum value

Table 6.3: Response Distribution Statistics

Response	min	Q1	$\tilde{x}$	Q3	max
Operational Availability	57.253	72.0600	76.820	79.4150	84.520
Abort Rate	0.017	0.0703	0.120	0.2250	0.364
Customer Wait Time (Hours)	45.628	56.6530	64.009	84.8330	129.251
Total Transportation Cost	11,580.000	37,247.0000	63,528.000	101,929.0000	198,805.000
Sorties Flown	238.240	283.5900	289.960	306.0400	346.680
Flight Hours	336.470	391.7600	418.490	439.3800	454.360
Times Failed	22.660	25.38200	26.448	29.1140	31.479
Backorders	578.000	2579.0000	3631.500	4717.5000	7478.000

In our experimental runs, 25% of the data for Operational Availability was above 79.42%, Abort Rate was below 7%, and Customer Wait Time was below 56 hours. As seen in these values, the data collected on each response covered a good range as well as a significant portion of the data near the realistic response values. The wide range of response values was due to the large number of factors used in our experiment. This means a large number of factor combinations would never logically be used; however, these factor combinations were important in our study of how the factors affected the response values. It is also important to mention that this experiment is a relative comparison; therefore, any small deviation from the actual mean will not affect the results presented in this report.

Table 6.4 provides more information about the distribution of the response data. The information provided in *Table 6.4* details the probabilities that the associated response fulfills the logical statement listed. For example, in the case of Operational Availability, $P(X >= 80) = 0.186$ indicates that across all design points there is an estimated probability of 0.186 that operational availability is greater than or equal to 80%. Also, 65% of the data for Customer Wait Time is below 72 hours or three days.

Table 6.4: Response Probabilities

Operational Availability	P(x >= 80)	0.185938
	P(x >= 75)	0.617188
Abort Rate	P(x <= .05)	0.175000
	P(x <= .15)	0.545313
	P(x <= .20)	0.701563
Customer Wait Time (Hours)	P(x <= 24)	0.046875
	P(x <= 72)	0.654688
	P(x <= 96)	0.873438
Total Transportation Cost	P(x <= 25,000)	0.154688
	P(x <= 50,000)	0.351563
	P(x <= 75,000)	0.612500

The relationship between some of the responses was also analyzed graphically. Of specific interest is the relationship between Total Transportation Cost and Operational Availability. To reduce the total number of plotted points from 640 to 128, the five replications of each design point were averaged, providing an estimate of the response for each design point. This will reduce the noise in the graph and provide a clearer picture of the data trends. *Figure 6.1* plots Operational Availability versus Total Transportation Cost and shows the diminishing return between Operational Availability and Total Cost. This is a common trend when comparing other performance metrics with total cost. There is usually a point at which spending increases faster than the improvement provided by the increased expenditure. Shipping plays a large roll in this trend of diminishing returns. There are many ways to reduce customer wait time and increase operational availability through expedited or express shipments like MICAP, but the cost of such practices grows at a rate that soon diminishes or even overtakes the value returned.

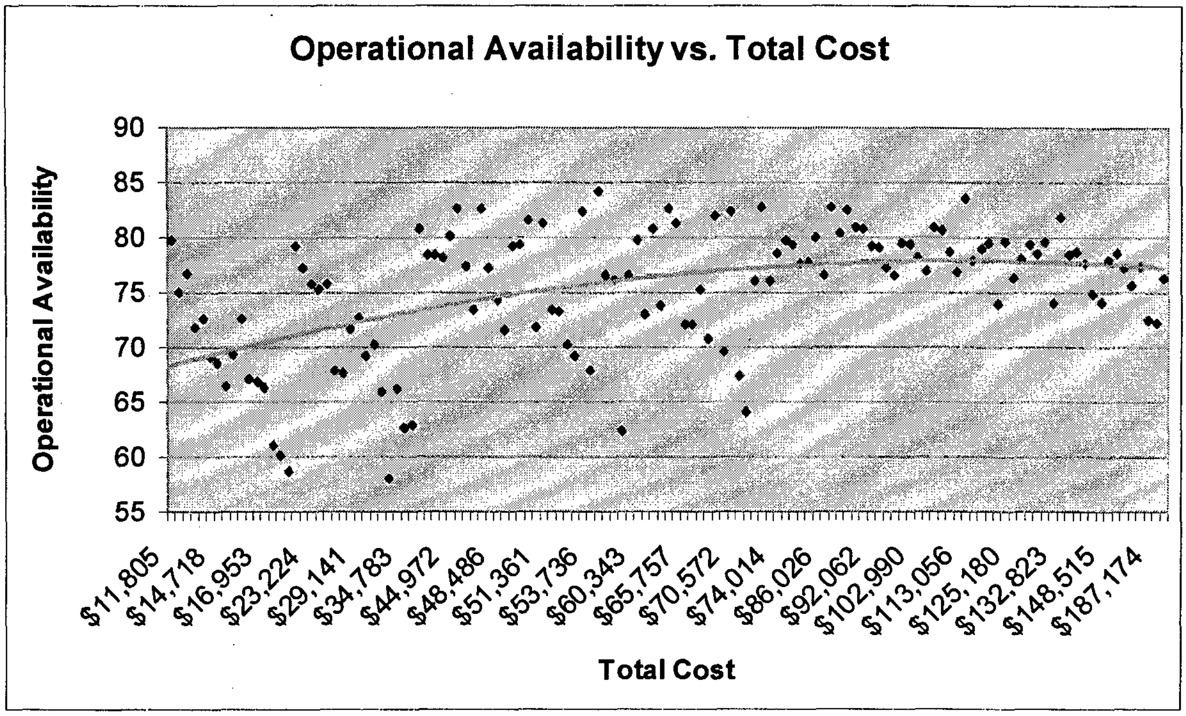

Figure 6.1: Operational Availability vs. Total Transportation Cost

Given the summary statistics on the behavior of each response across all scenarios, the next step was to quantify the effect that each factor had on each response. This was completed using the software package MINITAB®. A response surface model was developed for each response. The response surface model was developed by using the fractional factorial design to fit a linear regression equation between the factors of interest and the responses. Included in this analysis were all the main effects, along with all first-order interactions. As stated in the Experimental Design portion of this report, our experiment is a Resolution V Design. This high-resolution design allows the inclusion of all first-order interactions with complete confidence that there will be no confounding coefficients. A table was generated for each response, giving information about the effect that each factor had on that response, along with information on the goodness of fit of the model. *Appendix 2* contains all the summary statistics for each response as well as the MINITAB® regression output. Four important statistics were used to evaluate each factor's effect on the responses. The first statistic is the coefficient of multiple determination or R^2. This statistic is used to measure the adequacy of a multiple regression model. The coefficient of multiple determination measures the amount of variability in the data explained by the regression model. A good fitting model will usually have an R^2 value greater than or equal to 0.8 or 80%. This indicates the regression model accounts for

80% of the variation in the data. *Table 6.5* below lists the R^2 values given by the regression models, including all main effects and first-order interactions for the four main responses (Montgomery 1999).

Table 6.5: R^2 Values for the Initial Regression Models

Responses	R^2
Operational Availability	99.26%
Abort Rate	99.31%
Customer Wait Time	99.41%
Total Transportation Cost	99.47%

From the values presented in *Table 6.5*, it can be seen that almost all the variation in the data for each response can be explained by the main effects and first-order interaction terms of the response surface regression models. These models, while providing a good fit to the data, are very complicated. Each regression formula contains all the main effects, as well as their interactions coming to a total of 66 terms. The regression formulas take the general form of

$$Y = \beta_0 + \sum_{h=1}^{p} \beta_h x_h + \sum_{h=1}^{p} \beta_{h,h'} x_h x_{h'} + e$$

Equation 6.1

where Y is the response level, β_0 is the intercept term, x_h is the factor level, and β_h is the first-order factor coefficient describing the effect the factor has on the response, $\beta_{h,h'}$ is the second-order factor coefficient, and e represents the model error term. It can be seen from this general form that regression formulas containing 66 terms would be very cumbersome.

A good fit has been indicated, but the resulting regression formula is lengthy; however, a reduction in terms is possible. To reduce the number of terms included in the regression formulas, we begin by evaluating the contribution that each included factor has on the regression models. This is done using the second important statistic, the p-value. The p-value is the smallest level of α (alpha) at which the data can be deemed significant, where α is defined as the acceptable probability of error (Montgomery 1999). A p-value is generated for each main effect, as well as the first-order interactions. For this experiment, we chose an α of 0.01, and any factor with a p-value less than or equal to 0.01 was deemed to have a statistically significant effect on the response.

The third and fourth important statistics deal with the practical significance of the factor in relation to the response. These statistics are the estimated effects and the regression coefficients. The estimated effect is defined as the change in the response produced by a change in the factor (Montgomery 1999). The regression coefficient is the actual coefficient in the regression formula associated with the factor. An examination of these statistics for a factor indicates the estimated change in the response that will be experienced if the factor level is changed. In other words, these statistics describe the sensitivity of the response to changes in the associated factors. It is important to note that even if a factor is deemed statistically significant by the method discussed in the previous paragraph, an examination of the estimated effect and regression coefficient may reveal that the factor is practically insignificant.

With the knowledge gained through these four important statistics, the regression models for each response can be simplified greatly by removing the factors from the model that are neither statistically nor practically significant. The R^2 value is used as a metric for the change induced in the model's fit. Reducing the number of factors in the model will reduce the amount of variation explained by the model, but with the high R^2 values presented earlier for our full regression models, we can afford to be less explanatory for the sake of simplicity. *Table 6.6* associates a letter with each factor considered in the experiments. *Table 6.7* lists the simplified models developed for the four most important responses, along with the resulting R^2 value. The factor interactions are signified by an asterisk between two factors, like A*B. *Appendix 2* contains the complete MINITAB® output for each simplified regression model, listed by response.

Table 6.6: Letters Association

Factors	Associated Letter
Commercial Shipping	A
Sortie Duration	B
Sortie Frequency	C
MICAP	D
Repair Time	E

Factors	Associated Letter
Inventory Position	F
Time To Failure	G
Pre-/Post-Flight Maintenance	H
Unscheduled Maintenance	I
Local Repair	J
Lateral Transshipment	K

Table 6.7: Simplified Regression Models

Responses	Factors Included	R^2
Operational Availability	A, B, D, F, G, H, I, J, A*D, D*G, D*J	93.99%
Abort Rate	B, C, D, G, H, J	91.86%
Customer Wait Time	A, D, G, I, J, A*D, D*J	92.42%
Total Transportation Cost	A, D, F, G, J, K, A*D, D*F, D*G, D*J	97.16%

As seen in *Table 6.7*, a drastic simplification in the regression models was made, while the goodness of fit of the model changed very little. The initial regression models contained 66 terms, while the average number of terms included in the reduced models for these four responses is only 8.5. The factors listed in *Table 6.4* have a large impact both statistically and practically on the value of the associated response. The factors are the main contributors to the estimated value of the response variables. *Table 6.8* details the actual regression formulas generated from the simplified regression models. The formulas below can be used to estimate the value of the associated response given the factor levels included in the equation.

Table 6.8: Simplified Regression Equations

Responses	Simplified Regression Equation
Operational Availability	$Y = 75.279 + (-1.432\ A) + (-1.104\ B) + (-3.593\ D) + (0.549\ F) + (2.488\ G) + (0.566\ H) + (-1.05\ I) + (2.034\ J) + (-0.865\ (A * D)) + (0.684\ (D * G)) + (1.272\ (D * J))$
Abort Rate	$Y = 0.13783 + (0.03938\ B) + (0.06234\ C) + (0.01912\ D) + (-0.01295\ G) + (0.01821\ H) + (-0.01146\ J)$
Customer Wait Time	$Y = 72.783 + (5.8\ A) + (13.858\ D) + (-3.23\ G) + (3.749\ I) + (-8.116\ J) + (3.931\ (A * D)) + (-5.5\ (D * J))$
Total Transportation Cost	$Y = 72{,}244 + (-10{,}224\ A) + (-33{,}774\ D) + (-9{,}014\ F) + (-9{,}265\ G) + (-14{,}563\ J) + (-5{,}317\ K) + (-6{,}525\ (A * D)) + (8{,}793\ (D * F)) + (7{,}165\ (D * G)) + (10{,}978\ (D * J))$

Table 6.9 gives a breakdown of the most influential factors across all eight responses. The Number column lists the number of simplified regression models that include the associated factor, and the percent column lists the percentage of the simplified regression models that include the associated factor. *Table 6.9* takes into account all eight responses for which data was collected.

Table 6.9: Factor Influence All Responses

Factors	Number	Percent
A	6	75%
B	6	75%
C	4	50%
D	8	100%
E	0	0%
F	2	25%
G	8	100%
H	4	50%
I	2	25%
J	8	100%

Factors	Number	Percent
K	1	12.5%
A*D	4	50%
B*C	2	25%
D*F	1	12.5%
D*G	4	50%
D*J	6	75%

From *Table 6.9*, the most influential factors are MICAP, TTF and Local Repair. These factors are included in all the simplified regression models. This data gives an indication as to which factors, when changed, influence the greatest number of responses. It is notable that one factor, repair time, was not significant in any of the simplified models in comparison to the other factors. This is due to its relative length in time as compared to other delays that have more effect on the system, like shipping time. As noted in our model development section, the modeling of repair was simplified within our modeling approach. This result should not be taken to mean that repair is unimportant. In fact, this result indicates that future modeling should focus on developing the relationship between the repair process and operational availability. In other words, this is an area of the model that needs further development. The effects of the factors presented above will be further addressed in the Results and Assessment section of this report.

The effects of each factor are important in this study, but an overarching goal of this research was to determine the combination of factors that yield overall improved system performance. The aggregate function value method was used to combine performance metrics across the four major responses, yielding a total score or utility for each scenario (Daellenbach 1994). In the aggregate function method, each performance metric or response is converted to an overall utility value. These utility values form the basis for the comparison of the scenarios. Since the metrics (such as operational availability or total cost) do not have the same units or common scales or ranges, we must first convert the metrics to a common scale. While more complicated methods based upon utility theory exist to make the metrics have common units and scales, we used a simple linear transformation to convert the responses to values between 0.0 and 1.0. The linear transformation was completed by taking the response value for that specific design point, subtracting the minimum value for that response, and dividing that value by the difference between the response maximum and minimum (Equation 6.2).

$$X = \frac{(x - \min)}{(\max - \min)}$$

Equation 6.2

In Equation 6.2, X is the scaled response value, x is the response value for the design point, min is the minimum value of that response across all design points, and max is the maximum value of that response across all design points. Equation 6.3 shows what this calculation would look like for Operational Availability.

$$X = \frac{(x - 57)}{(85 - 57)}$$

Equation 6.3

After scaling the responses, a weight of importance was assigned to each response. These weights should range from 0 to 1, and should add to 1. The weights can be varied to illustrate the trade-offs between the importance of the various responses. This allows the development of a total utility function by multiplying the weight for the response by the scaled value of the response and summing across the responses. For example, let TP be the total performance of the scenario and let IP_i be the individual performance of the i^{th} scaled response (like operational availability). Then the total performance of the scenario is shown as

$$TP = \sum_i IP_i$$

Equation 6.4

There are responses that may indicate a negative scenario performance, in other words a higher response value is considered negative performance. It is important when developing the scaled values to invert the responses that have this property.

In our experiments, we chose as the four responses operational availability, abort rate, customer wait time, and total transportation cost as the most important in gauging model performance. Each response was scaled linearly to be between 0 and 1 per the process discussed earlier, yielding a percent performance in each response for each scenario. Weights for the four responses were developed as follows: Operational Availability (0.4), Abort Rate (0.15), Customer Wait Time (0.15), and Total

Transportation Cost (0.3). A high value was placed on balancing operational availability and total cost. The total performance for all 128 design points was computed. The nine alternatives possessing the highest utility were selected for further study. *Table 6.10* outlines the top nine scenarios, along with their associated factor levels. Please refer to *Table 6.6* for the factor associated with each letter. In *Table 6.10*, -1 refers to the low value of the factor and 1 refers to the high value of the factor. Please refer to *Table 5.1* and *Table 5.2* for a description of the factors, levels and expected results. *Table 6.11* details the response values for each of the nine scenarios, along with the calculated utility.

Table 6.10: Top Nine Scenarios

Scenario	A	B	C	D	E	F	G	H	I	J	K
1	-1	-1	-1	-1	-1	1	1	1	-1	1	-1
2	1	-1	-1	1	1	1	1	-1	-1	1	1
3	-1	-1	-1	-1	1	1	1	1	1	1	1
4	-1	-1	-1	-1	-1	1	-1	-1	-1	1	1
5	-1	-1	-1	1	1	-1	1	1	-1	1	1
6	1	-1	-1	1	-1	1	1	-1	1	1	-1
7	1	-1	-1	-1	-1	1	1	-1	-1	-1	1
8	1	-1	-1	-1	-1	-1	1	-1	-1	1	-1
9	1	-1	-1	-1	1	-1	1	-1	1	1	1

Table 6.11: Scenario Response Values and Utility

Scenario	OA	Total Transport Cost	CWT (Hrs)	Abort Rate	Utility	Weighted OA	Weighted Total Cost	Weighted CWT	Weighted Abort Rate
1	84.27%	$54,182.38	46.25	2.43%	91.60%	39.03%	23.145%	14.78%	14.65%
2	79.72%	$11,805.00	64.67	2.04%	89.17%	32.96%	29.87%	11.53%	14.81%
3	82.38%	$53,400.07	53.57	2.96%	87.69%	36.50%	23.27%	13.49%	14.43%
4	82.03%	$69,136.82	46.33	2.09%	86.38%	36.05%	20.77%	14.77%	14.79%
5	80.76%	$41,718.00	59.42	3.76%	86.01%	34.34%	25.12%	12.46%	14.09%

Scenario	OA	Total Transport Cost	CWT (Hrs)	Abort Rate	Utility	Weighted OA	Weighted Total Cost	Weighted CWT	Weighted Abort Rate
6	79.21%	$20,254.80	66.25	1.96%	86.91%	32.28%	28.53%	11.25%	14.85%
7	82.82%	$72,480.70	52.41	1.75%	85.96%	37.09%	20.24%	13.69%	14.94%
8	82.31%	$70,572.38	54.45	1.77%	85.22%	36.42%	20.54%	13.33%	14.93%
9	81.38%	$65,627.57	57.24	1.80%	84.26%	35.17%	21.33%	12.84%	14.92%

To statistically compare these alternatives, a second set of replications was run using Arena's Process Analyzer ©. The number of replications needed to yield a 95% confidence interval on utility of plus or minus 0.002 was calculated. This calculation was done by first determining which scenario had the highest utility standard deviation across its five replications. Then a sample size calculation was completed using the highest calculated standard deviation, giving a sample size of 61. This means that 61 runs of each scenario will yield utility values that we are 95% confident are within plus or minus 0.002 of the actual mean.

7 Results and Assessment

The results for the top nine rated scenarios allow a multiple comparison procedure to be performed that can determine the best scenario. This comparison yields insights as to the combinations of factors that result in the most appealing response values based upon our utility calculation. *Table 7.1* lists the utility values calculated for the nine scenarios. *Figure 7.1* shows a box plot of the results from the Process Analyzer.

Table 7.1: Top Nine Utilities

Scenario	Utility
1	89.54%
2	87.74%
3	85.85%
4	85.08%
5	85.05%
6	84.67%
7	84.39%
8	83.40%
9	82.78%

Utility by Scenario

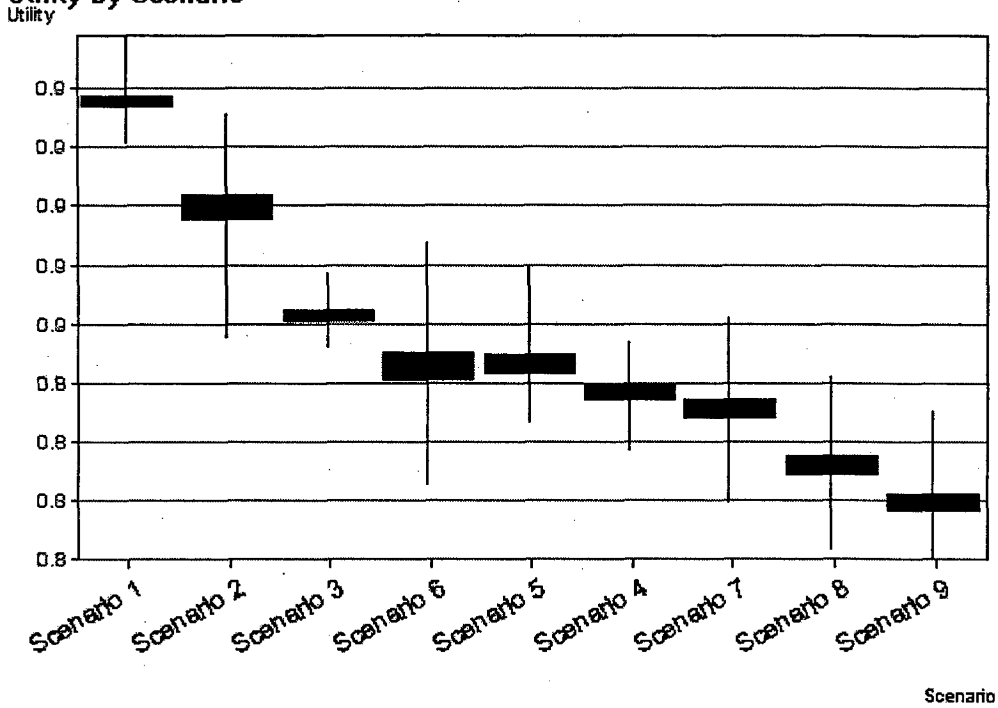

Figure 7.1: Utility Box Plot

From the scenario analysis, Scenario 1 is the best combination of factor levels under the current weighting system. Sensitivity analysis was performed to determine how sensitive the utility values were to changes in the values of the weights. In this sensitivity analysis, the weights for Operational Availability and Total Transportation Cost were altered, leaving the other two weights at their current values. It was determined that Scenario 1 and Scenario 2 were dominant over the other seven; however, Scenario 2 became the best alternative when the weight for both Operational Availability and Total Transportation Cost were set at 0.35. This is due to the extremely low cost in Scenario 2. This low cost is attributable to a few of the factor levels: Shipping Option – TL; MICAP – off; and Transshipment – off. The two scenarios shared these factor levels: Inventory Position – Local; and Repair Local – High. The greatest utility was gained by placing more spare part inventory at the base level, along with more of the repair resources at the base level. Utilizing a TL service and removing all express options achieved the lowest cost. The low-cost scenario did sacrifice some operational availability, but the sensitivity analysis of the weights demonstrates that the sacrifice was not practically significant. The costing method, however, does not take into account the cost of shifting repair resources to the base level. This consideration should be an area of future study and model development.

One scenario stands out in this group of nine, Scenario 7. It stands out because it is the only scenario with Repair Local set to its low value. It is interesting to note that this scenario has one of the highest operational availability rates, but also has the highest cost. This is due to the fact that the shipping option is LTL and MICAP is on. While parts are accumulating to be shipped LTL, MICAP picks up the slack.

Another notable scenario is Scenario 5. This scenario is one of three that have Inventory Position set to depot. Also interesting is the fact that the Shipping Option is LTL, while both MICAP and Transshipment are turned off. As in Scenario 2, the tradeoff between Operational Availability and Total Transportation Cost is seen. With the express shipping options turned off, cost is reduced, but Operational Availability suffers. In this case, Scenario 5 does not overtake Scenario 1 until the weight for Total Transportation Cost reaches 0.6, and it never overtakes Scenario 2.

8 Summary and Conclusions

The MIME repairable parts system is a complicated interaction of processes, which in the case of military supply chains must be both robust and very reliable. Due to the educational community's interest in the complexity of the system, along with military investment, the MIME system is one that has been studied in some depth over the years. Through the course of these studies, a few mathematical- and simulation-based models have been developed to further explore the MIME system. The mathematical models developed by Sherbrooke, Graves, Slay, and others provide valuable information about the MIME system; however, these mathematical models must make many limiting assumptions that hamper their ability to provide detailed analysis. The development of simulation-based models allows the relaxation of these limiting assumptions, providing a model that captures more of the subtleties and variation in the system. Simulation-based models are also both flexible and expandable, allowing for an extensive experimental design.

For the purposes of this report, a simulation model was developed based upon the Air Force's MIME repairable parts system. This simulation model encompasses a structure that includes 24 individual SRUs composing six LRUs, 432 aircraft, six bases, and one depot. The experiments outlined in *Section 5* were designed to provide information about the largest contributing factors associated with Operational Availability, Abort Rate, Customer Wait Time, and Total Transportation Cost. We chose to vary 11 factors in this experiment (*Table 5.1*). To explore how each factor, along with its interactions, affected the four indicators of model performance, a fractional factorial experimental design was used. With this experimental design were 128 individual design points, and each design point was replicated five times, yielding a total of 640 simulation runs. The information provided by these simulation runs allows the creation of linear response surface regression models for each response. The regression models provide the ability to evaluate the effect each factor has on each response.

A second set of experiments was completed in an attempt to find the most appealing combination of factors. For each design point, the four response values were scaled to be between zero and one, weighted by importance and added together, yielding a utility value. The utility value gave us a means by which to compare the 128 design points. From the 128 design points, the top nine were chosen based upon utility, and a second set of 65 replications was run for each of the nine. The second set of experiments provided statistical information on the best performing combination of factors based upon utility.

From our experimental runs, the largest contributing factors to operational availability, abort rate, customer wait time, and total transportation cost are MICAP, TTF, local repair, shipping option, sortie duration, and inventory position. Time to failure and sortie duration are obvious contributors. It is easy to see that the more reliable your parts are in a MIME system, the better your system will perform. Along the same lines, if sortie duration is increased, more flight hours will accrue per aircraft, resulting in an increase in failures. The other four factors have greater implications.

The MICAP factor was one of the most influential factors in our experiment. This factor simulated the use of express carriers to expedite shipping times. Over the past decade, the logistical defense-related budgets have been reduced. This, in turn, has had an effect on the way the military supply chain operates. Inventory levels in the supply chain have been falling along with the budgets. Today, the military supply chain is being asked to be "more flexible and responsive" with less inventory and "at a lower total cost"(Condon 1999). The pressure to reduce both inventory and spending has induced a lot of stress on the military supply chain. As the inventory levels fell through the 1990s and into the present, it became harder to maintain a reliable flow of material. The Air Force has compensated for the low inventory levels by using express carriers, and they have been successful; however the cost of relying on these express carriers is very high. The cost of MICAP shipments was the largest cost component in our simulation model.

Figure 6.1 illustrates the diminishing returns relationship between transportation cost and operational availability. The cost of MICAP shipments is a large driver in the shape of this curve. If the MICAP cost component were removed, this curve would take on a more linear shape. The diminishing returns relationship would not disappear, but it would be reduced. Reducing the role MICAP plays in the Air Force supply chain will both reduce cost greatly and force new opportunities for improvement to be explored. In our second set of experimental runs, the second-best performing scenario, Scenario 2, did not use MICAP. This scenario used the TL shipping option and yielded a cost that was four and a half times lower than Scenario 1 with a comparable operational availability.

This drastic improvement in cost warrants exploration. In their article, "MICAP Shipping Policies: Are they optimal from a cost standpoint?" Masciulli and Cunningham (2001) indicate that a redefinition of the policies governing MICAP shipments, along with selection rules when it comes to choosing a commercial carrier, would be beneficial from a cost standpoint. Their research indicated only a small percentage change in cost, while our research indicates drastic cost reductions through greatly reducing, if not eliminating, MICAP without drastic effects on the other three responses. Our experiment indicates that the emphases should not be internal to the MICAP policies, but should instead be external, focusing upon the inventory policies, inventory structure, and other lower-cost shipping options.

Many alternatives can be explored to reduce the Air Force's reliance on MICAP shipments. In their article, "Why So Many AWP LRUs?" Carter and London (2002) explore the SRU inventory levels. They say that current inventory levels for specific SRUs are not meeting demand, while others are overstocked. They state that probability of LRU failure should drive inventory levels. They also make the point that with repairable parts, when setting inventory levels, a cost balance should be reached between the one-time cost of purchasing the item and the cost of a backorder for that item. Larvick (2000) discusses the logistics system as a whole in his journal article. In this discussion, Larvick describes "reach-back capability." This refers to the greater ability of the upper-echelon levels to respond to variation at the lower levels. In his model, increased sortie duration and frequency result in more failures at the base level. He refers to reach-back as the ability of the higher echelons to respond to this change. This concept ties directly into the idea of increased supply chain visibility. Murphy (1999) explores the possibility of "Collocating Air Force weapon systems inventory with the Defense Logistics Agency premium service facility." These articles touch on just a few areas where there are opportunities for system improvements that could result in a supply chain that is robust and reliable, but does not rely so heavily on costly MICAP shipments.

The two other shipping factors investigated in our experiments are shipping option (LTL/TL) and transshipment. The shipping option factor explored the difference in using LTL versus TL shipping. In our experiments, a cost benefit was seen when using the TL shipping option. In fact, the lowest costs were realized in scenarios using TL shipping. These cost differences, however, were overshadowed by the cost of MICAP shipping. In the same light, the transshipment factor did not play a large role in our experiments. This again was due mainly to the fact that the MICAP option had a dominating effect. In future models, these shipping options, as well as direct shipments, should be explored in a more detailed fashion outside the shadow of MICAP.

The inventory position factor also played an important role in the response values. Of the top nine performing scenarios, six of them had more of the total system inventory shifted to the base level. This worked in conjunction with the local repair factor, which was set to its high value in eight of the nine scenarios. In other words, the best performing scenarios had more repair resources at the base level along with more of the spares inventory being pushed to the bases. The cost of this combination of factor values was not fully explored in our experiments. Extending more of the repair resources to the base level would be a costly operation, but the benefits could be far-reaching. This, along with other inventory and repair options, must be investigated to a further extent in future models. Also, the concepts of lean logistics and velocity management covered in the literature review will be important topics in future studies about inventory and resource positioning.

Many opportunities exist for expansion of the simulation model developed for this report. The following are areas where model expansion would be of benefit to future studies:

- Repair process
- Cannibalization
- Queue prioritization
- Sortie generation and assignment
- Inventory policies and costing
- Shipping alternatives
- Policies
- Interaction

Future work has already been funded and is in the beginning stages for expanding the model presented in this report to explore the sortie generation process. The goal of this new project is to extend the current simulation and mathematical modeling methodologies to assist unit-level logistics managers in analyzing the effects of different resource allocation policies and identify risks in logistical plans. The model will encompass sortie generation, maintenance activities, and the effect of limited equipment and inventory.

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Appendix 1: Model Inputs with Distributions and Parameters

Baseline Model Inputs and Distributions

Parts	
Number of LRUs	6
Number SRUs-LRU1	4
Number SRUs-LRU2	4
Number SRUs-LRU3	4
Number SRUs-LRU4	4
Number SRUs-LRU5	4
Number SRUs-LRU6	4
Time to Failure Distribution for SRUs in Hours - Each distribution corresponds to a set of eight SRUs within the system.	Exponential (300) Exponential (400) Exponential (500)
Inventory at Base Level for all SRUs	3
Inventory at Depot Level for all SRUs	20
Repair Time Distribution for all SRUs in Hours	Exponential (8)
Number of Repair Resources at the Base Level	Unlimited Capacity
Number of Repair Resources at the Depot Level	Unlimited Capacity
Queuing rules for repair	Backordered parts are given top priority in the repair process
Probability that a part can be repaired at the base level	.01

Shipping

Number	Distribution (Hours)	Description
1	TRIA(12,81.6,184.8)	This distribution is used to generate shipping times between bases in the same region.
2	TRIA(31.2,170.4,348)	This distribution is used to generate shipping times between the depot and the bases in Region 1.
3	TRIA(76.8, 266.4, 453.6)	This distribution is used to generate shipping times between the depot and the bases in Region 2. This distribution is also used to generate the shipping time between bases not in the same region.

Shipping Time Distribution Matrix in Hours

	Base 1	Base 2	Base 3	Base 4	Base 5	Base 6
Base 1	0	1	1	3	3	3
Base 2	1	0	1	3	3	3
Base 3	1	1	0	3	3	3
Base 4	3	3	3	0	1	1
Base 5	3	3	3	1	0	1
Base 6	3	3	3	1	1	0
Depot	2	2	2	3	3	3

MICAP Shipping Time in Hours	TRIA(22, 24, 26)
Maximum LTL Load in Number of SRUs	20
Minimum LTL Load in Percent of Max Load	0.2
Structure (refer to *Figure 4.1*)	
Number of Planes Per Unit	24
Number of Units Per Squadron	3

Number of Squadrons Per Base	1
Number of Bases	6
Number of Regions	2
Number of Bases Per Region	3
Number of Depots	1
Sorties	
Number of Sorties Assigned Per Base Per Day Distribution	ANINT(Unit(56,67))
Sortie Length Distribution in Hours	Triangular (.333, 1.747, 2)
Number of Runs (groups of sorties) per Day	2
First Run Scheduled at	8:00
Second Run Scheduled at	12:00
Phase Inspection	
Accrued Flight Hours Before Base Phase Inspection	290-305 Flight Hours
Base Phase Inspection Time Distribution in Days	Triangular (5,7,10)
Repair Resources Required for Phase Inspection	50
Queuing Rules for Phase Inspection	First In First Out
Pre-Flight Operations	
Refuel	Triangular (8,10,12) minutes
Weapon Load	Triangular(25,30,35) minutes
Pre-Flight	Triangular(50,60,70) minutes
Engine Start, Final Systems Check and Taxiing	Triangular(7,10,12) minutes
Takeoff	Triangular(2,3,4) minutes
Post-Flight Operations	
Landing	Triangular(14,15,16) minutes
Parking and Recovery	Triangular(5,7,9)-2 minutes
Final Parking	2 Minutes with LRU clock stopped

Service and Debrief	Triangular(45,60,75) minutes
Unscheduled Maintenance Operations	
Troubleshooting	Triangular(20,24,30) minutes
Remove Part	Triangular(45,60,70) minutes
Wait for part to issue from supply	Triangular(.5,2,2.5) hours
Delay for paperwork	Triangular(5,10,15) minutes
Installation	Triangular(60,84,120) minutes
Operational Check	Triangular(15,20,25) minutes
Signoff Discrepancy	Triangular(5,10,15) minutes
Document Corrective Action	Triangular(5,10,15) minutes

Appendix 2: Summary Statistics for Responses and MINITAB® Response Output

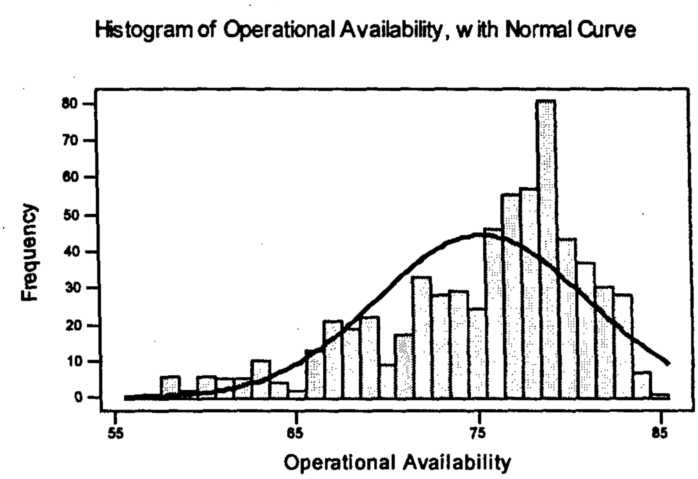
MINITAB® Response Output

Factors	Associated Letter
Commercial Shipping	A
Sortie Duration	B
Sortie Frequency	C
MICAP	D
Repair Time	E
Inventory Position	F
Time To Failure	G
Pre-/Post-Flight Maintenance	H
Unscheduled Maintenance	I
Local Repair	J
Lateral Transshipment	K

Operational Availability

Descriptive Statistics: Operational Availability

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3	P(x >= 80)	P(x >= 75)
640	75.279	76.820	75.661	5.754	0.227	57.253	84.520	72.060	79.415	.185938	0.617188



Fractional Factorial Fit: Operational Availability vs. A, B, C, D, E, F, G, H, I, J, K

Estimated Effects and Coefficients for Operational Availability

Term	Effect	Coef	SE Coef	T	P
Constant		75.279	0.02072	3633.57	0.000
A	-2.864	-1.432	0.02072	-69.13	0.000
B	-2.209	-1.104	0.02072	-53.31	0.000
C	-0.966	-0.483	0.02072	-23.31	0.000
D	-7.187	-3.593	0.02072	-173.45	0.000
E	-0.032	-0.016	0.02072	-0.78	0.437

F	1.098	0.549	0.02072	26.51	0.000
G	4.975	2.488	0.02072	120.07	0.000
H	1.131	0.566	0.02072	27.30	0.000
I	-2.101	-1.050	0.02072	-50.70	0.000
J	4.068	2.034	0.02072	98.17	0.000
K	0.269	0.134	0.02072	6.49	0.000
A*B	-0.191	-0.096	0.02072	-4.61	0.000
A*C	-0.173	-0.086	0.02072	-4.17	0.000
A*D	-1.730	-0.865	0.02072	-41.75	0.000
A*E	0.022	0.011	0.02072	0.54	0.591
A*F	-0.210	-0.105	0.02072	-5.06	0.000
A*G	0.519	0.260	0.02072	12.53	0.000
A*H	0.169	0.085	0.02072	4.08	0.000
A*I	0.053	0.026	0.02072	1.28	0.202
A*J	0.408	0.204	0.02072	9.84	0.000
A*K	0.009	0.005	0.02072	0.22	0.826
B*C	0.827	0.414	0.02072	19.96	0.000
B*D	-0.909	-0.454	0.02072	-21.93	0.000
B*E	-0.039	-0.020	0.02072	-0.95	0.344
B*F	-0.015	-0.008	0.02072	-0.37	0.712
B*G	0.297	0.148	0.02072	7.16	0.000
B*H	-0.239	-0.119	0.02072	-5.76	0.000
B*I	-0.100	-0.050	0.02072	-2.41	0.016
B*J	0.410	0.205	0.02072	9.89	0.000
B*K	0.068	0.034	0.02072	1.65	0.100
C*D	-0.208	-0.104	0.02072	-5.03	0.000
C*E	-0.018	-0.009	0.02072	-0.44	0.661
C*F	-0.313	-0.156	0.02072	-7.54	0.000
C*G	-0.029	-0.014	0.02072	-0.69	0.489
C*H	0.363	0.182	0.02072	8.77	0.000
C*I	0.065	0.032	0.02072	1.57	0.117
C*J	0.124	0.062	0.02072	2.98	0.003
C*K	0.026	0.013	0.02072	0.62	0.534
D*E	0.064	0.032	0.02072	1.54	0.124
D*F	0.602	0.301	0.02072	14.52	0.000
D*G	1.369	0.684	0.02072	33.03	0.000

D*H	0.812	0.406	0.02072	19.59	0.000
D*I	0.337	0.168	0.02072	8.13	0.000
D*J	2.544	1.272	0.02072	61.41	0.000
D*K	-1.133	-0.566	0.02072	-27.34	0.000
E*F	-0.099	-0.050	0.02072	-2.40	0.017
E*G	-0.002	-0.001	0.02072	-0.04	0.966
E*H	-0.061	-0.031	0.02072	-1.48	0.139
E*I	-0.020	-0.010	0.02072	-0.48	0.634
E*J	0.037	0.019	0.02072	0.90	0.370
E*K	0.025	0.013	0.02072	0.61	0.543
F*G	0.146	0.073	0.02072	3.53	0.000
F*H	0.013	0.006	0.02072	0.31	0.755
F*I	-0.010	-0.005	0.02072	-0.25	0.805
F*J	0.294	0.147	0.02072	7.10	0.000
F*K	-0.337	-0.168	0.02072	-8.13	0.000
G*H	-0.351	-0.176	0.02072	-8.48	0.000
G*I	0.048	0.024	0.02072	1.16	0.247
G*J	-0.418	-0.209	0.02072	-10.09	0.000
G*K	-0.116	-0.058	0.02072	-2.79	0.005
H*I	0.095	0.047	0.02072	2.29	0.022
H*J	-0.452	-0.226	0.02072	-10.92	0.000
H*K	0.049	0.025	0.02072	1.19	0.233
I*J	-0.166	-0.083	0.02072	-4.01	0.000
I*K	-0.035	-0.017	0.02072	-0.84	0.402
J*K	-0.175	-0.088	0.02072	-4.23	0.000

Analysis of Variance for Operational Availability

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	18230.5	18230.5	1657.32	6E+03	0.000
2-Way Interactions	55	2768.1	2768.1	50.33	183.21	0.000
Residual Error	573	157.4	157.4	0.27		
Lack of Fit	61	95.4	95.4	1.56	12.93	0.000
Pure Error	512	62.0	62.0	0.12		
Total	639	21156.0				

R^2 - 99.26%

Fractional Factorial Fit: Operational Availability vs. A, B, C, D, E, F, G, H, I, J

Estimated Effects and Coefficients for Operational Availability

Term	Effect	Coef	SE Coef	T	P
Constant		75.279	0.05626	1338.02	0.000
A	-2.864	-1.432	0.05626	-25.46	0.000
B	-2.209	-1.104	0.05626	-19.63	0.000
D	-7.187	-3.593	0.05626	-63.87	0.000
F	1.098	0.549	0.05626	9.76	0.000
G	4.975	2.488	0.05626	44.21	0.000
H	1.131	0.566	0.05626	10.05	0.000
I	-2.101	-1.050	0.05626	-18.67	0.000
J	4.068	2.034	0.05626	36.15	0.000
A*D	-1.730	-0.865	0.05626	-15.37	0.000
D*G	1.369	0.684	0.05626	12.16	0.000
D*J	2.544	1.272	0.05626	22.61	0.000

Analysis of Variance for Operational Availability

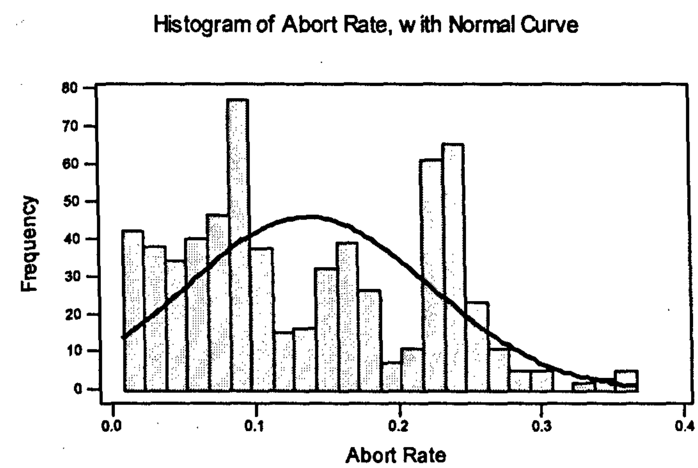
Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	8	18069.5	18069.5	2258.69	1E+03	0.000
2-Way Interactions	3	1814.3	1814.3	604.76	298.52	0.000
Residual Error	628	1272.2	1272.2	2.03		
Lack of Fit	116	1210.3	1210.3	10.43	86.22	0.000
Pure Error	512	62.0	62.0	0.12		
Total	639	21156.0				

R^2 - 93.99%

Abort Rate

Descriptive Statistics: Abort Rate

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3	P(x <= .05)	P(x <= .15)	P(x <= .2)
640	75.279	76.820	75.661	5.754	0.227	57.253	84.520	72.060	79.415	.185938	0.617188	0.701563



Fractional Factorial Fit: Abort Rate

Estimated Effects and Coefficients for Abort Rate

Term	Effect	Coef	SE Coef	T	P
Constant		0.13783	0.000290	475.09	0.000
A	0.01825	0.00913	0.000290	31.46	0.000
B	0.07877	0.03938	0.000290	135.75	0.000
C	0.12468	0.06234	0.000290	214.90	0.000
D	0.03824	0.01912	0.000290	65.91	0.000
E	-0.00074	-0.00037	0.000290	-1.28	0.202
F	-0.00605	-0.00303	0.000290	-10.43	0.000

G	-0.02591	-0.01295	0.000290	-44.66	0.000
H	0.03642	0.01821	0.000290	62.76	0.000
I	0.00968	0.00484	0.000290	16.69	0.000
J	-0.02292	-0.01146	0.000290	-39.50	0.000
K	0.00017	0.00009	0.000290	0.30	0.767
A*B	-0.00238	-0.00119	0.000290	-4.11	0.000
A*C	0.00027	0.00014	0.000290	0.47	0.640
A*D	0.01388	0.00694	0.000290	23.92	0.000
A*E	-0.00004	-0.00002	0.000290	-0.07	0.944
A*F	-0.00019	-0.00010	0.000290	-0.33	0.743
A*G	0.00658	0.00329	0.000290	11.34	0.000
A*H	-0.00186	-0.00093	0.000290	-3.20	0.001
A*I	0.00108	0.00054	0.000290	1.87	0.062
A*J	-0.00615	-0.00308	0.000290	-10.60	0.000
A*K	0.00020	0.00010	0.000290	0.34	0.734
B*C	0.01858	0.00929	0.000290	32.03	0.000
B*D	-0.00250	-0.00125	0.000290	-4.30	0.000
B*E	0.00027	0.00014	0.000290	0.47	0.640
B*F	0.00067	0.00034	0.000290	1.16	0.247
B*G	0.00348	0.00174	0.000290	5.99	0.000
B*H	-0.00993	-0.00497	0.000290	-17.12	0.000
B*I	-0.00112	-0.00056	0.000290	-1.92	0.055
B*J	0.00115	0.00057	0.000290	1.98	0.049
B*K	0.00063	0.00032	0.000290	1.09	0.275
C*D	0.00282	0.00141	0.000290	4.86	0.000
C*E	-0.00057	-0.00029	0.000290	-0.99	0.325
C*F	0.00448	0.00224	0.000290	7.72	0.000
C*G	-0.00169	-0.00085	0.000290	-2.91	0.004
C*H	0.00688	0.00344	0.000290	11.87	0.000
C*I	0.00064	0.00032	0.000290	1.10	0.270
C*J	-0.00015	-0.00007	0.000290	-0.25	0.800
C*K	-0.00121	-0.00060	0.000290	-2.08	0.038
D*E	0.00247	0.00124	0.000290	4.26	0.000
D*F	-0.00435	-0.00218	0.000290	-7.50	0.000
D*G	-0.01361	-0.00680	0.000290	-23.46	0.000
D*H	0.00753	0.00376	0.000290	12.97	0.000

D*I	0.00095	0.00047	0.000290	1.63	0.103
D*J	-0.01845	-0.00923	0.000290	-31.80	0.000
D*K	0.00460	0.00230	0.000290	7.92	0.000
E*F	-0.00133	-0.00067	0.000290	-2.30	0.022
E*G	0.00002	0.00001	0.000290	0.04	0.970
E*H	-0.00003	-0.00001	0.000290	-0.05	0.961
E*I	0.00863	0.00431	0.000290	14.87	0.000
E*J	-0.00005	-0.00002	0.000290	-0.08	0.936
E*K	-0.00016	-0.00008	0.000290	-0.27	0.784
F*G	-0.00080	-0.00040	0.000290	-1.38	0.167
F*H	-0.00062	-0.00031	0.000290	-1.06	0.289
F*I	-0.00055	-0.00027	0.000290	-0.94	0.346
F*J	-0.00145	-0.00072	0.000290	-2.49	0.013
F*K	0.00212	0.00106	0.000290	3.65	0.000
G*H	-0.00167	-0.00084	0.000290	-2.88	0.004
G*I	-0.00180	-0.00090	0.000290	-3.11	0.002
G*J	0.00732	0.00366	0.000290	12.62	0.000
G*K	0.00073	0.00037	0.000290	1.27	0.206
H*I	0.00227	0.00114	0.000290	3.92	0.000
H*J	-0.00362	-0.00181	0.000290	-6.23	0.000
H*K	-0.00069	-0.00035	0.000290	-1.19	0.234
I*J	-0.00050	-0.00025	0.000290	-0.86	0.392
I*K	0.00008	0.00004	0.000290	0.13	0.893
J*K	0.00082	0.00041	0.000290	1.41	0.160

Analysis of Variance for Abort Rate

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	4.19188	4.19188	0.381080	7E+03	0.000
2-Way Interactions	55	0.25985	0.25985	0.004725	87.71	0.000
Residual Error	573	0.03086	0.03086	0.000054		
Lack of Fit	61	0.02365	0.02365	0.000388	27.54	0.000
Pure Error	512	0.00721	0.00721	0.000014		
Total	639	4.48259				

R^2 - 99.31%

Fractional Factorial Fit: Abort Rate vs. B, C, D, G, H, J

Estimated Effects and Coefficients for Abort (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		0.13783	0.000949	145.21	0.000
B	0.07877	0.03938	0.000949	41.49	0.000
C	0.12468	0.06234	0.000949	65.68	0.000
D	0.03824	0.01912	0.000949	20.14	0.000
G	-0.02591	-0.01295	0.000949	-13.65	0.000
H	0.03642	0.01821	0.000949	19.18	0.000
J	-0.02292	-0.01146	0.000949	-12.07	0.000

Analysis of Variance for Abort (Coded Units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	6	4.11761	4.11761	0.686269	1E+03	0.000
Residual Error	633	0.36498	0.36498	0.000577		
Lack of Fit	57	0.33270	0.33270	0.005837	104.14	0.000
Pure Error	576	0.03228	0.03228	0.000056		
Total	639	4.48259				

R^2 - 91.86%

Estimated Effects and Coefficients for Abort (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		0.13783	0.000748	184.26	0.000
B	0.07877	0.03938	0.000748	52.65	0.000
C	0.12468	0.06234	0.000748	83.34	0.000
D	0.03824	0.01912	0.000748	25.56	0.000
G	-0.02591	-0.01295	0.000748	-17.32	0.000
H	0.03642	0.01821	0.000748	24.34	0.000
J	-0.02292	-0.01146	0.000748	-15.32	0.000
B*C	0.01858	0.00929	0.000748	12.42	0.000
D*G	-0.01361	-0.00680	0.000748	-9.10	0.000
D*J	-0.01845	-0.00923	0.000748	-12.33	0.000

Analysis of Variance for Abort (Coded Units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	6	4.11761	4.11761	0.686269	2E+03	0.000
2-Way Interactions	3	0.13938	0.13938	0.046459	129.74	0.000
Residual Error	630	0.22560	0.22560	0.000358		
Lack of Fit	54	0.19332	0.19332	0.003580	63.87	0.000
Pure Error	576	0.03228	0.03228	0.000056		
Total	639	4.48259				

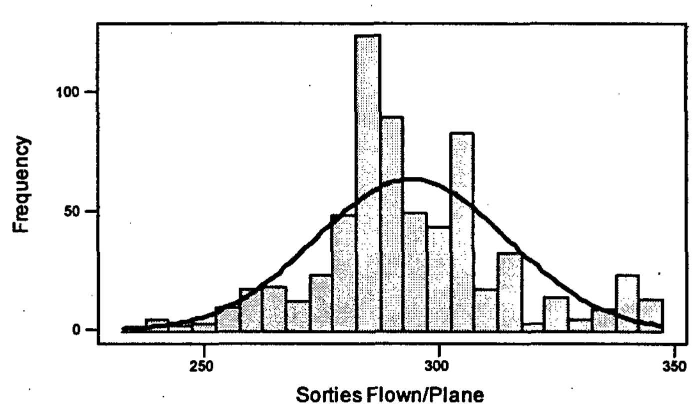
R^2 - 94.97%

Sorties Flown/Plane

Descriptive Statistics: Sorties Flown/Plane

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3
640	294.26	289.96	293.89	20.21	0.80	238.24	346.68	283.59	306.04

Histogram of Sorties Flow n/Plane, w ith Normal Curve



Estimated Effects and Coefficients for Sorties Flown

Term	Effect	Coef	SE Coef	T	P
Constant		294.26	0.1029	2860.67	0.000
A	-6.25	-3.13	0.1029	-30.40	0.000
B	-27.47	-13.73	0.1029	-133.52	0.000
C	9.42	4.71	0.1029	45.77	0.000
D	-13.20	-6.60	0.1029	-64.16	0.000
E	0.32	0.16	0.1029	1.55	0.121
F	1.95	0.98	0.1029	9.50	0.000
G	8.59	4.30	0.1029	41.78	0.000
H	-12.48	-6.24	0.1029	-60.65	0.000

I	-3.30	-1.65	0.1029	-16.05	0.000
J	7.82	3.91	0.1029	38.00	0.000
K	0.01	0.01	0.1029	0.05	0.957
A*B	0.77	0.39	0.1029	3.74	0.000
A*C	-0.66	-0.33	0.1029	-3.22	0.001
A*D	-4.79	-2.40	0.1029	-23.29	0.000
A*E	-0.02	-0.01	0.1029	-0.11	0.913
A*F	-0.55	-0.27	0.1029	-2.65	0.008
A*G	-2.55	-1.28	0.1029	-12.39	0.000
A*H	0.76	0.38	0.1029	3.67	0.000
A*I	-0.42	-0.21	0.1029	-2.02	0.044
A*J	1.97	0.99	0.1029	9.58	0.000
A*K	-0.09	-0.04	0.1029	-0.42	0.677
B*C	-8.76	-4.38	0.1029	-42.57	0.000
B*D	1.10	0.55	0.1029	5.36	0.000
B*E	-0.11	-0.06	0.1029	-0.54	0.588
B*F	-0.29	-0.15	0.1029	-1.43	0.154
B*G	-1.19	-0.60	0.1029	-5.80	0.000
B*H	3.66	1.83	0.1029	17.77	0.000
B*I	0.44	0.22	0.1029	2.14	0.033
B*J	-0.53	-0.27	0.1029	-2.60	0.010
B*K	-0.20	-0.10	0.1029	-0.97	0.331
C*D	-2.18	-1.09	0.1029	-10.62	0.000
C*E	0.22	0.11	0.1029	1.05	0.296
C*F	-1.30	-0.65	0.1029	-6.33	0.000
C*G	1.32	0.66	0.1029	6.43	0.000
C*H	-3.49	-1.75	0.1029	-16.97	0.000
C*I	-0.55	-0.28	0.1029	-2.67	0.008
C*J	0.77	0.38	0.1029	3.72	0.000
C*K	0.40	0.20	0.1029	1.95	0.051
D*E	-0.88	-0.44	0.1029	-4.27	0.000
D*F	1.27	0.63	0.1029	6.15	0.000
D*G	4.73	2.37	0.1029	23.00	0.000
D*H	-2.52	-1.26	0.1029	-12.26	0.000
D*I	-0.38	-0.19	0.1029	-1.84	0.066
D*J	6.31	3.16	0.1029	30.68	0.000

D*K	-1.61	-0.80	0.1029	-7.82	0.000
E*F	0.46	0.23	0.1029	2.23	0.026
E*G	0.01	0.01	0.1029	0.07	0.945
E*H	0.03	0.01	0.1029	0.13	0.896
E*I	-3.06	-1.53	0.1029	-14.85	0.000
E*J	0.03	0.01	0.1029	0.13	0.899
E*K	0.04	0.02	0.1029	0.19	0.851
F*G	0.33	0.16	0.1029	1.59	0.112
F*H	0.21	0.10	0.1029	1.01	0.311
F*I	0.21	0.11	0.1029	1.04	0.300
F*J	0.90	0.45	0.1029	4.36	0.000
F*K	-0.73	-0.37	0.1029	-3.55	0.000
G*H	0.46	0.23	0.1029	2.23	0.026
G*I	0.63	0.32	0.1029	3.08	0.002
G*J	-2.51	-1.26	0.1029	-12.22	0.000
G*K	-0.22	-0.11	0.1029	-1.09	0.278
H*I	-0.76	-0.38	0.1029	-3.68	0.000
H*J	1.21	0.61	0.1029	5.88	0.000
H*K	0.23	0.12	0.1029	1.13	0.257
I*J	0.17	0.09	0.1029	0.84	0.401
I*K	-0.24	-0.12	0.1029	-1.17	0.242
J*K	-0.28	-0.14	0.1029	-1.35	0.179

Analysis of Variance for Sorties Flown

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	217927	217927	19811.5	3E+03	0.000
2-Way Interactions	55	39084	39084	710.6	104.93	0.000
Residual Error	573	3880	3880	6.8		
Lack of Fit	61	3038	3038	49.8	30.26	0.000
Pure Error	512	843	843	1.6		
Total	639	260891				

R^2 - 98.51%

Fractional Factorial Fit: Sorties Flown/Plane vs. A, B, C, D, G, H, J

Estimated Effects and Coefficients for Sorties (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		294.26	0.2199	1338.24	0.000
A	-6.25	-3.13	0.2199	-14.22	0.000
B	-27.47	-13.73	0.2199	-62.46	0.000
C	9.42	4.71	0.2199	21.41	0.000
D	-13.20	-6.60	0.2199	-30.01	0.000
G	8.59	4.30	0.2199	19.54	0.000
H	-12.48	-6.24	0.2199	-28.37	0.000
J	7.82	3.91	0.2199	17.77	0.000
A*D	-4.79	-2.40	0.2199	-10.90	0.000
B*C	-8.76	-4.38	0.2199	-19.92	0.000
D*G	4.73	2.37	0.2199	10.76	0.000
D*J	6.31	3.16	0.2199	14.35	0.000

Analysis of Variance for Sorties (Coded Units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	7	215554	215554	30793.4	995.11	0.000
2-Way Interactions	4	25904	25904	6476.0	209.28	0.000
Residual Error	628	19433	19433	30.9		
Lack of Fit	52	15518	15518	298.4	43.90	0.000
Pure Error	576	3916	3916	6.8		
Total	639	260891				

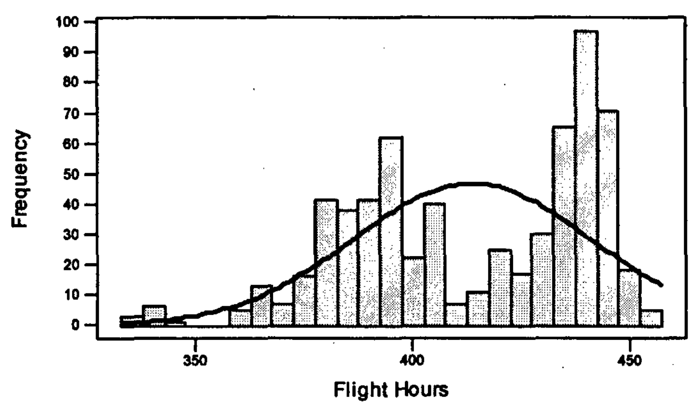
R^2 - 92.55%

Flight Hours/Plane

Descriptive Statistics: Flight Hours/Plane

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3
640	413.66	418.49	414.84	27.33	1.08	336.47	454.36	391.76	439.38

Histogram of Flight Hours, with Normal Curve



Estimated Effects and Coefficients for Flight Hours

Term	Effect	Coef	SE Coef	T	P
Constant		413.658	0.1488	2779.29	0.000
A	-8.774	-4.387	0.1488	-29.48	0.000
B	36.774	18.387	0.1488	123.54	0.000
C	12.152	6.076	0.1488	40.82	0.000
D	-18.498	-9.249	0.1488	-62.14	0.000
E	0.427	0.213	0.1488	1.43	0.152
F	2.738	1.369	0.1488	9.20	0.000
G	12.001	6.001	0.1488	40.32	0.000
H	-17.126	-8.563	0.1488	-57.53	0.000
I	-4.592	-2.296	0.1488	-15.42	0.000

J	10.968	5.484	0.1488	36.85	0.000
K	-0.044	-0.022	0.1488	-0.15	0.883
A*B	0.252	0.126	0.1488	0.85	0.397
A*C	-0.997	-0.498	0.1488	-3.35	0.001
A*D	-6.700	-3.350	0.1488	-22.51	0.000
A*E	-0.040	-0.020	0.1488	-0.13	0.893
A*F	-0.622	-0.311	0.1488	-2.09	0.037
A*G	-3.125	-1.562	0.1488	-10.50	0.000
A*H	0.878	0.439	0.1488	2.95	0.003
A*I	-0.581	-0.291	0.1488	-1.95	0.051
A*J	2.794	1.397	0.1488	9.39	0.000
A*K	-0.085	-0.043	0.1488	-0.29	0.774
B*C	-11.185	-5.593	0.1488	-37.58	0.000
B*D	-0.155	-0.077	0.1488	-0.52	0.603
B*E	-0.132	-0.066	0.1488	-0.44	0.658
B*F	-0.149	-0.074	0.1488	-0.50	0.618
B*G	-0.571	-0.286	0.1488	-1.92	0.056
B*H	3.558	1.779	0.1488	11.95	0.000
B*I	0.209	0.104	0.1488	0.70	0.484
B*J	0.243	0.121	0.1488	0.82	0.415
B*K	-0.283	-0.141	0.1488	-0.95	0.342
C*D	-2.699	-1.349	0.1488	-9.07	0.000
C*E	0.304	0.152	0.1488	1.02	0.308
C*F	-1.887	-0.944	0.1488	-6.34	0.000
C*G	1.811	0.905	0.1488	6.08	0.000
C*H	-4.585	-2.292	0.1488	-15.40	0.000
C*I	-0.655	-0.327	0.1488	-2.20	0.028
C*J	0.878	0.439	0.1488	2.95	0.003
C*K	0.526	0.263	0.1488	1.77	0.078
D*E	-1.176	-0.588	0.1488	-3.95	0.000
D*F	1.775	0.887	0.1488	5.96	0.000
D*G	6.714	3.357	0.1488	22.55	0.000
D*H	-3.718	-1.859	0.1488	-12.49	0.000
D*I	-0.587	-0.293	0.1488	-1.97	0.049
D*J	8.965	4.483	0.1488	30.12	0.000
D*K	-2.198	-1.099	0.1488	-7.39	0.000

E*F	0.625	0.312	0.1488	2.10	0.036
E*G	0.070	0.035	0.1488	0.24	0.814
E*H	0.012	0.006	0.1488	0.04	0.968
E*I	-4.038	-2.019	0.1488	-13.57	0.000
E*J	0.055	0.028	0.1488	0.19	0.853
E*K	0.393	0.197	0.1488	1.32	0.187
F*G	0.557	0.278	0.1488	1.87	0.062
F*H	0.000	0.000	0.1488	0.00	0.999
F*I	0.310	0.155	0.1488	1.04	0.298
F*J	1.217	0.609	0.1488	4.09	0.000
F*K	-1.044	-0.522	0.1488	-3.51	0.000
G*H	0.707	0.353	0.1488	2.37	0.018
G*I	0.898	0.449	0.1488	3.02	0.003
G*J	-3.546	-1.773	0.1488	-11.91	0.000
G*K	-0.289	-0.144	0.1488	-0.97	0.332
H*I	-1.045	-0.523	0.1488	-3.51	0.000
H*J	1.750	0.875	0.1488	5.88	0.000
H*K	0.334	0.167	0.1488	1.12	0.263
I*J	0.268	0.134	0.1488	0.90	0.368
I*K	-0.319	-0.160	0.1488	-1.07	0.284
J*K	-0.367	-0.184	0.1488	-1.23	0.218

Analysis of Variance for Flight Hours

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	400893	400893	36444.8	3E+03	0.000
2-Way Interactions	55	68389	68389	1243.4	87.71	0.000
Residual Error	573	8124	8124	14.2		
Lack of Fit	61	6312	6312	103.5	29.24	0.000
Pure Error	512	1812	1812	3.5		
Total	639	477406				

R^2 - 98.30%

Fractional Factorial Fit: Flight Hours vs. A, B, C, D, G, H, J

Estimated Effects and Coefficients for Flight (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		413.658	0.2902	1425.51	0.000
A	-8.774	-4.387	0.2902	-15.12	0.000
B	36.774	18.387	0.2902	63.36	0.000
C	12.152	6.076	0.2902	20.94	0.000
D	-18.498	-9.249	0.2902	-31.87	0.000
G	12.001	6.001	0.2902	20.68	0.000
H	-17.126	-8.563	0.2902	-29.51	0.000
J	10.968	5.484	0.2902	18.90	0.000
A*D	-6.700	-3.350	0.2902	-11.54	0.000
B*C	-11.185	-5.593	0.2902	-19.27	0.000
D*G	6.714	3.357	0.2902	11.57	0.000
D*J	8.965	4.483	0.2902	15.45	0.000

Analysis of Variance for Flight (Coded Units)

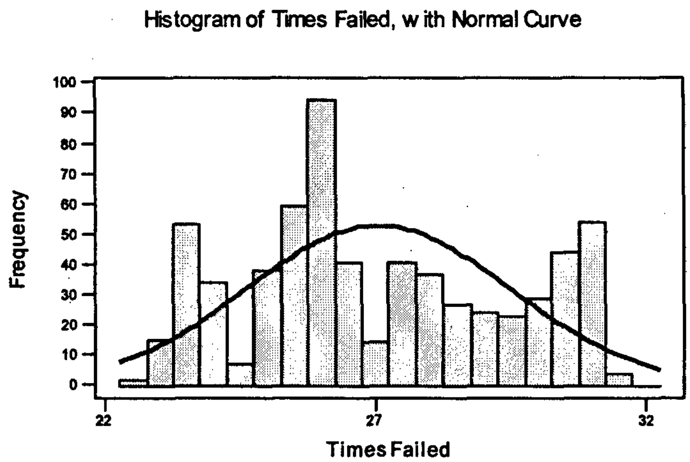
Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	7	396291	396291	56613.0	1E+03	0.000
2-Way Interactions	4	47271	47271	11817.8	219.29	0.000
Residual Error	628	33844	33844	53.9		
Lack of Fit	52	26266	26266	505.1	38.39	0.000
Pure Error	576	7578	7578	13.2		
Total	639	477406				

R^2 - 92.91%

Times Failed/Plane

Descriptive Statistics: Times Failed/Plane

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3
640	27.050	26.448	27.040	2.417	0.096	22.660	31.479	25.382	29.114



Estimated Effects and Coefficients for Times Failed

Term	Effect	Coef	SE Coef	T	P
Constant		27.050	0.01266	2137.31	0.000
A	-0.498	-0.249	0.01266	-19.69	0.000
B	1.492	0.746	0.01266	58.95	0.000
C	0.811	0.406	0.01266	32.05	0.000
D	-1.077	-0.539	0.01266	-42.56	0.000
E	0.029	0.015	0.01266	1.15	0.252
F	0.158	0.079	0.01266	6.26	0.000
G	-3.980	-1.990	0.01266	-157.24	0.000
H	-0.593	-0.297	0.01266	-23.45	0.000

I	-0.267	-0.134	0.01266	-10.55	0.000
J	0.644	0.322	0.01266	25.46	0.000
K	-0.005	-0.003	0.01266	-0.22	0.829
A*B	-0.005	-0.003	0.01266	-0.21	0.835
A*C	-0.015	-0.007	0.01266	-0.59	0.559
A*D	-0.463	-0.231	0.01266	-18.29	0.000
A*E	-0.006	-0.003	0.01266	-0.22	0.823
A*F	-0.052	-0.026	0.01266	-2.05	0.041
A*G	-0.175	-0.087	0.01266	-6.90	0.000
A*H	-0.008	-0.004	0.01266	-0.33	0.742
A*I	-0.016	-0.008	0.01266	-0.65	0.517
A*J	0.151	0.076	0.01266	5.98	0.000
A*K	-0.011	-0.005	0.01266	-0.43	0.669
B*C	-0.758	-0.379	0.01266	-29.94	0.000
B*D	0.016	0.008	0.01266	0.63	0.531
B*E	-0.025	-0.012	0.01266	-0.98	0.329
B*F	-0.024	-0.012	0.01266	-0.95	0.344
B*G	-0.186	-0.093	0.01266	-7.34	0.000
B*H	0.222	0.111	0.01266	8.77	0.000
B*I	0.045	0.022	0.01266	1.77	0.077
B*J	-0.009	-0.005	0.01266	-0.37	0.709
B*K	-0.028	-0.014	0.01266	-1.12	0.262
C*D	-0.199	-0.099	0.01266	-7.85	0.000
C*E	0.012	0.006	0.01266	0.47	0.638
C*F	-0.086	-0.043	0.01266	-3.41	0.001
C*G	0.042	0.021	0.01266	1.68	0.094
C*H	-0.292	-0.146	0.01266	-11.53	0.000
C*I	-0.073	-0.037	0.01266	-2.89	0.004
C*J	0.048	0.024	0.01266	1.89	0.059
C*K	0.045	0.022	0.01266	1.77	0.078
D*E	-0.097	-0.049	0.01266	-3.85	0.000
D*F	0.115	0.058	0.01266	4.55	0.000
D*G	0.524	0.262	0.01266	20.70	0.000
D*H	-0.276	-0.138	0.01266	-10.91	0.000
D*I	-0.061	-0.031	0.01266	-2.43	0.016
D*J	0.511	0.255	0.01266	20.17	0.000

D*K	-0.129	-0.064	0.01266	-5.09	0.000
E*F	0.032	0.016	0.01266	1.25	0.212
E*G	0.024	0.012	0.01266	0.97	0.335
E*H	0.008	0.004	0.01266	0.31	0.757
E*I	-0.272	-0.136	0.01266	-10.73	0.000
E*J	-0.031	-0.015	0.01266	-1.21	0.227
E*K	0.007	0.003	0.01266	0.26	0.795
F*G	0.015	0.008	0.01266	0.60	0.547
F*H	-0.002	-0.001	0.01266	-0.07	0.941
F*I	0.014	0.007	0.01266	0.53	0.594
F*J	0.100	0.050	0.01266	3.94	0.000
F*K	-0.077	-0.039	0.01266	-3.06	0.002
G*H	0.126	0.063	0.01266	4.98	0.000
G*I	0.088	0.044	0.01266	3.48	0.001
G*J	-0.294	-0.147	0.01266	-11.63	0.000
G*K	-0.007	-0.004	0.01266	-0.28	0.779
H*I	-0.054	-0.027	0.01266	-2.13	0.034
H*J	0.125	0.063	0.01266	4.95	0.000
H*K	-0.004	-0.002	0.01266	-0.14	0.888
I*J	0.009	0.005	0.01266	0.37	0.714
I*K	-0.025	-0.012	0.01266	-0.97	0.333
J*K	-0.015	-0.007	0.01266	-0.58	0.560

Analysis of Variance for Times Failed

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	3360.02	3360.02	305.456	3E+03	0.000
2-Way Interactions	55	312.70	312.70	5.685	55.46	0.000
Residual Error	573	58.74	58.74	0.103		
Lack of Fit	61	30.62	30.62	0.502	9.14	0.000
Pure Error	512	28.12	28.12	0.055		
Total	639	3731.46				

R^2 - 98.43%

Fractional Factorial Fit: Times Failed vs. B, C, D, G, H, J

Estimated Effects and Coefficients for Times (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		27.050	0.02486	1087.90	0.000
B	1.492	0.746	0.02486	30.00	0.000
C	0.811	0.406	0.02486	16.31	0.000
D	-1.077	-0.539	0.02486	-21.66	0.000
G	-3.980	-1.990	0.02486	-80.04	0.000
H	-0.593	-0.297	0.02486	-11.93	0.000
J	0.644	0.322	0.02486	12.96	0.000
B*C	-0.758	-0.379	0.02486	-15.24	0.000
D*G	0.524	0.262	0.02486	10.53	0.000
D*J	0.511	0.255	0.02486	10.27	0.000

Analysis for Variance for Times (Coded Units)

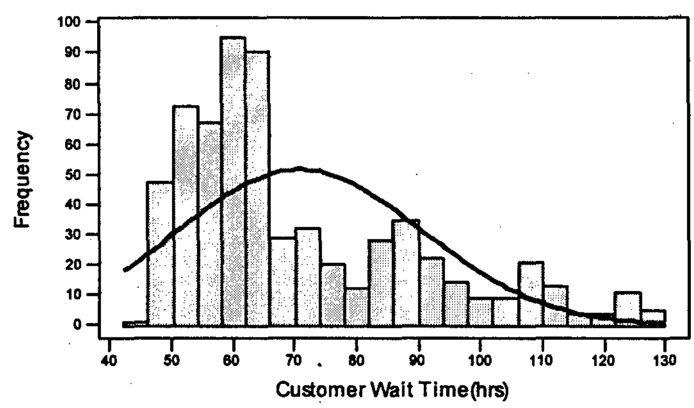
Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	6	3304.69	3304.69	550.782	1E+03	0.000
2-Way Interactions	3	177.50	177.50	59.165	149.53	0.000
Residual Error	630	249.27	249.27	0.396		
Lack of Fit	54	195.11	195.11	3.613	38.42	0.000
Pure Error	576	54.16	54.16	0.094		
Total	639	3731.46				

R^2 - 93.32%

Customer Wait Time/Failure

Descriptive Statistics: Customer Wait Time/Failure

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3	P(x <= 24)	P(x >= 72)	P(x >= 96)
640	70.783	64.009	69.359	19.799	0.783	45.628	129.251	56.653	84.833	0.046875	0.654688	0.873438



Estimated Effects and Coefficients for Customer Wait Time

Term	Effect	Coef	SE Coef	T	P
Constant		70.783	0.06367	1111.78	0.000
A	11.600	5.800	0.06367	91.10	0.000
B	3.077	1.539	0.06367	24.17	0.000
C	1.157	0.578	0.06367	9.09	0.000
D	27.716	13.858	0.06367	217.67	0.000
E	0.116	0.058	0.06367	0.91	0.362
F	-4.308	-2.154	0.06367	-33.83	0.000
G	-6.461	-3.230	0.06367	-50.74	0.000
H	-1.760	-0.880	0.06367	-13.82	0.000

I	7.497	3.749	0.06367	58.88	0.000
J	-16.232	-8.116	0.06367	-127.48	0.000
K	-0.536	-0.268	0.06367	-4.21	0.000
A*B	0.422	0.211	0.06367	3.32	0.001
A*C	0.385	0.192	0.06367	3.02	0.003
A*D	7.861	3.931	0.06367	61.74	0.000
A*E	-0.045	-0.022	0.06367	-0.35	0.726
A*F	0.648	0.324	0.06367	5.09	0.000
A*G	-0.796	-0.398	0.06367	-6.25	0.000
A*H	-0.234	-0.117	0.06367	-1.84	0.066
A*I	-0.038	-0.019	0.06367	-0.30	0.765
A*J	-2.544	-1.272	0.06367	-19.98	0.000
A*K	0.149	0.074	0.06367	1.17	0.243
B*C	-0.911	-0.455	0.06367	-7.15	0.000
B*D	2.347	1.174	0.06367	18.43	0.000
B*E	0.046	0.023	0.06367	0.36	0.718
B*F	0.264	0.132	0.06367	2.07	0.039
B*G	-0.177	-0.088	0.06367	-1.39	0.165
B*H	0.255	0.127	0.06367	2.00	0.046
B*I	0.076	0.038	0.06367	0.60	0.549
B*J	-1.005	-0.503	0.06367	-7.89	0.000
B*K	-0.150	-0.075	0.06367	-1.17	0.241
C*D	0.936	0.468	0.06367	7.35	0.000
C*E	-0.054	-0.027	0.06367	-0.42	0.671
C*F	2.098	1.049	0.06367	16.47	0.000
C*G	0.077	0.039	0.06367	0.61	0.545
C*H	-0.452	-0.226	0.06367	-3.55	0.000
C*I	-0.148	-0.074	0.06367	-1.16	0.247
C*J	-0.318	-0.159	0.06367	-2.50	0.013
C*K	-0.014	-0.007	0.06367	-0.11	0.911
D*E	-0.069	-0.034	0.06367	-0.54	0.591
D*F	-2.587	-1.293	0.06367	-20.32	0.000
D*G	-4.458	-2.229	0.06367	-35.01	0.000
D*H	-1.546	-0.773	0.06367	-12.14	0.000
D*I	-0.557	-0.279	0.06367	-4.38	0.000
D*J	-11.000	-5.500	0.06367	-86.38	0.000

D*K	4.278	2.139	0.06367	33.60	0.000
E*F	0.180	0.090	0.06367	1.41	0.158
E*G	-0.087	-0.043	0.06367	-0.68	0.496
E*H	0.030	0.015	0.06367	0.23	0.816
E*I	0.565	0.283	0.06367	4.44	0.000
E*J	-0.029	-0.014	0.06367	-0.22	0.822
E*K	0.085	0.042	0.06367	0.66	0.506
F*G	-0.837	-0.419	0.06367	-6.57	0.000
F*H	-0.174	-0.087	0.06367	-1.36	0.174
F*I	-0.011	-0.005	0.06367	-0.09	0.931
F*J	-1.035	-0.518	0.06367	-8.13	0.000
F*K	1.366	0.683	0.06367	10.73	0.000
G*H	0.499	0.250	0.06367	3.92	0.000
G*I	0.044	0.022	0.06367	0.35	0.728
G*J	1.518	0.759	0.06367	11.92	0.000
G*K	0.252	0.126	0.06367	1.98	0.049
H*I	-0.117	-0.059	0.06367	-0.92	0.358
H*J	0.972	0.486	0.06367	7.63	0.000
H*K	-0.125	-0.063	0.06367	-0.98	0.325
I*J	0.279	0.140	0.06367	2.19	0.029
I*K	0.178	0.089	0.06367	1.40	0.162
J*K	0.425	0.213	0.06367	3.34	0.001

Analysis of Variance for Customer Wait Time

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	207514	207514	18864.9	7E+03	0.000
2-Way Interactions	55	41499	41499	754.5	290.86	0.000
Residual Error	573	1486	1486	2.6		
Lack of Fit	61	920	920	15.1	13.64	0.000
Pure Error	512	566	566	1.1		
Total	639	250500				

R^2 - 99.41%

Fractional Factorial Fit: Customer Wait Time (Hrs) vs. A, D, G, I, J

Estimated Effects and Coefficients for Customer (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		70.783	0.2166	326.74	0.000
A	11.600	5.800	0.2166	26.77	0.000
D	27.716	13.858	0.2166	63.97	0.000
G	-6.461	-3.230	0.2166	-14.91	0.000
I	7.497	3.749	0.2166	17.30	0.000
J	-16.232	-8.116	0.2166	-37.46	0.000
A*D	7.861	3.931	0.2166	18.14	0.000
D*J	-11.000	-5.500	0.2166	-25.39	0.000

Analysis of Variance for Customer (Coded Units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	5	202271	202271	40454.3	1E+03	0.000
2-Way Interactions	2	29246	29246	14623.0	486.86	0.000
Residual Error	632	18982	18982	30.0		
Lack of Fit	24	6094	6094	253.9	11.98	0.000
Pure Error	608	12888	12888	21.2		
Total	639	250500				

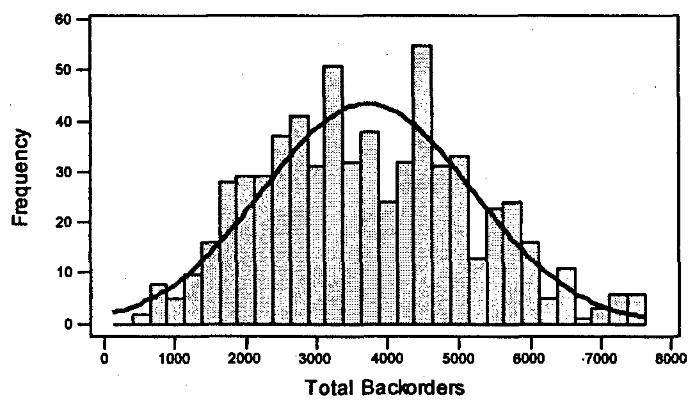
R^2 - 92.42%

Backorders

Descriptive Statistics: Backorders

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3
640	3713.2	3631.5	3686.9	1466.9	58.0	578.0	7478.0	2579.0	4717.5

Histogram of Total Backorders, with Normal Curve



Estimated Effects and Coefficients for Total Backorders

Term	Effect	Coef	SE Coef	T	P
Constant		3713.2	5.070	732.34	0.000
A	948.7	474.3	5.070	93.55	0.000
B	580.9	290.5	5.070	57.29	0.000
C	238.3	119.1	5.070	23.50	0.000
D	973.6	486.8	5.070	96.02	0.000
E	13.4	6.7	5.070	1.32	0.187
F	-1479.8	-739.9	5.070	-145.93	0.000
G	-1388.4	-694.2	5.070	-136.92	0.000
H	-262.1	-131.1	5.070	-25.85	0.000

I	-113.7	-56.8	5.070	-11.21	0.000
J	-1249.3	-624.7	5.070	-123.20	0.000
K	-473.6	-236.8	5.070	-46.70	0.000
A*B	21.8	10.9	5.070	2.15	0.032
A*C	58.9	29.5	5.070	5.81	0.000
A*D	-39.5	-19.7	5.070	-3.89	0.000
A*E	-2.6	-1.3	5.070	-0.26	0.797
A*F	19.4	9.7	5.070	1.91	0.056
A*G	-111.4	-55.7	5.070	-10.98	0.000
A*H	-28.9	-14.4	5.070	-2.85	0.005
A*I	0.4	0.2	5.070	0.04	0.966
A*J	84.8	42.4	5.070	8.37	0.000
A*K	-44.4	-22.2	5.070	-4.38	0.000
B*C	-221.4	-110.7	5.070	-21.84	0.000
B*D	131.7	65.8	5.070	12.98	0.000
B*E	-8.2	-4.1	5.070	-0.81	0.418
B*F	-25.5	-12.8	5.070	-2.52	0.012
B*G	-99.9	-50.0	5.070	-9.85	0.000
B*H	49.9	25.0	5.070	4.92	0.000
B*I	5.8	2.9	5.070	0.57	0.570
B*J	-77.2	-38.6	5.070	-7.61	0.000
B*K	-49.6	-24.8	5.070	-4.89	0.000
C*D	8.8	4.4	5.070	0.86	0.388
C*E	3.2	1.6	5.070	0.32	0.752
C*F	-98.1	-49.0	5.070	-9.67	0.000
C*G	-4.2	-2.1	5.070	-0.41	0.681
C*H	-90.5	-45.3	5.070	-8.93	0.000
C*I	-26.4	-13.2	5.070	-2.60	0.010
C*J	-98.2	-49.1	5.070	-9.69	0.000
C*K	-4.4	-2.2	5.070	-0.43	0.666
D*E	-42.2	-21.1	5.070	-4.16	0.000
D*F	84.1	42.0	5.070	8.29	0.000
D*G	-123.4	-61.7	5.070	-12.17	0.000
D*H	-163.8	-81.9	5.070	-16.15	0.000
D*I	-43.9	-22.0	5.070	-4.33	0.000
D*J	-154.4	-77.2	5.070	-15.22	0.000

D*K	118.2	59.1	5.070	11.66	0.000
E*F	19.7	9.8	5.070	1.94	0.053
E*G	4.1	2.1	5.070	0.41	0.683
E*H	66.2	33.1	5.070	6.53	0.000
E*I	-39.2	-19.6	5.070	-3.87	0.000
E*J	-14.0	-7.0	5.070	-1.38	0.167
E*K	-1.3	-0.6	5.070	-0.13	0.899
F*G	78.6	39.3	5.070	7.75	0.000
F*H	-9.7	-4.8	5.070	-0.95	0.340
F*I	0.2	0.1	5.070	0.02	0.986
F*J	-90.4	-45.2	5.070	-8.91	0.000
F*K	103.6	51.8	5.070	10.21	0.000
G*H	79.9	39.9	5.070	7.88	0.000
G*I	67.9	33.9	5.070	6.69	0.000
G*J	64.6	32.3	5.070	6.37	0.000
G*K	102.3	51.2	5.070	10.09	0.000
H*I	-11.2	-5.6	5.070	-1.11	0.268
H*J	87.4	43.7	5.070	8.61	0.000
H*K	-7.3	-3.6	5.070	-0.72	0.474
I*J	14.2	7.1	5.070	1.40	0.161
I*K	11.7	5.8	5.070	1.15	0.250
J*K	89.7	44.8	5.070	8.84	0.000

Analysis of Variance for Total Backorders

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	1316228624	1316228624	119657148	7E+03	0.000
2-Way Interactions	55	49397412	49397412	898135	54.59	0.000
Residual Error	573	9427328	9427328	16453		
Lack of Fit	61	4299221	4299221	70479	7.04	0.000
Pure Error	512	5128107	5128107	10016		
Total	639	1375053364				

R^2 - 99.31%

Fractional Factorial Fit: Total Backorders vs. A, B, D, F, G, J

Estimated Effects and Coefficients for Customer (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		3713.2	16.99	218.61	0.000
A	948.7	474.3	16.99	27.93	0.000
B	580.9	290.5	16.99	17.10	0.000
D	973.6	486.8	16.99	28.66	0.000
F	-1479.8	-739.9	16.99	-43.56	0.000
G	-1388.4	-694.2	16.99	-40.87	0.000
J	-1249.3	-624.7	16.99	-36.78	0.000

Analysis of Variance for Total (Coded Units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	6	1258171824	1258171824	209695304	1E+03	0.000
Residual Error	633	116881540	116881540	184647		
Lack of Fit	57	63296879	63296879	1110472	11.94	0.000
Pure Error	576	53584661	53584661	93029		
Total	639	1375053364				

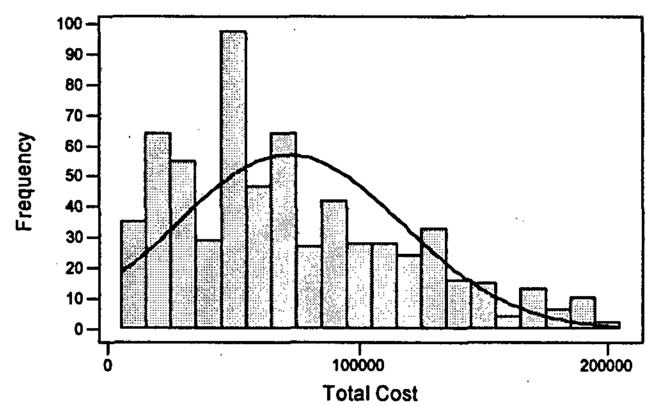
R^2 - 91.50%

Total Transportation Cost

Descriptive Statistics: Total Cost

N	Mean	Median	TrMean	StDev	SE Mean	Minimum	Maximum	Q1	Q3
640	72,244	63,528	69,609	44,770	1,770	11,580	198,805	37,247	101,929

Histogram of Total Cost, with Normal Curve



Fractional Factorial Fit: Total Transportation Cost vs. A, B, ...

Estimated Effects and Coefficients for Total (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		72244	136.2	530.36	0.000
A	-20447	-10224	136.2	-75.05	0.000
B	6817	3408	136.2	25.02	0.000
C	3506	1753	136.2	12.87	0.000
D	-67548	-33774	136.2	-247.94	0.000
E	634	317	136.2	2.33	0.020
F	-18029	-9014	136.2	-66.18	0.000
G	-18531	-9265	136.2	-68.02	0.000
H	-1754	-877	136.2	-6.44	0.000
I	-976	-488	136.2	-3.58	0.000
J	-29126	-14563	136.2	-106.91	0.000
K	-10635	-5317	136.2	-39.04	0.000
A*B	-180	-90	136.2	-0.66	0.510
A*C	2372	1186	136.2	8.71	0.000
A*D	-13050	-6525	136.2	-47.90	0.000
A*E	-65	-33	136.2	-0.24	0.811
A*F	-1296	-648	136.2	-4.76	0.000
A*G	-1438	-719	136.2	-5.28	0.000
A*H	-175	-87	136.2	-0.64	0.522
A*I	28	14	136.2	0.10	0.919
A*J	2	1	136.2	0.01	0.993
A*K	-228	-114	136.2	-0.84	0.403
B*C	-3715	-1858	136.2	-13.64	0.000
B*D	-4951	-2476	136.2	-18.17	0.000
B*E	-413	-206	136.2	-1.51	0.130
B*F	-395	-198	136.2	-1.45	0.147
B*G	-1448	-724	136.2	-5.32	0.000
B*H	942	471	136.2	3.46	0.001
B*I	99	49	136.2	0.36	0.717
B*J	-1695	-848	136.2	-6.22	0.000
B*K	-795	-397	136.2	-2.92	0.004

C*D	-2780	-1390	136.2	-10.20	0.000
C*E	49	25	136.2	0.18	0.857
C*F	-2326	-1163	136.2	-8.54	0.000
C*G	22	11	136.2	0.08	0.935
C*H	-1012	-506	136.2	-3.72	0.000
C*I	-136	-68	136.2	-0.50	0.619
C*J	-2261	-1131	136.2	-8.30	0.000
C*K	193	96	136.2	0.71	0.480
D*E	-821	-411	136.2	-3.01	0.003
D*F	17585	8793	136.2	64.55	0.000
D*G	14331	7165	136.2	52.60	0.000
D*H	795	397	136.2	2.92	0.004
D*I	714	357	136.2	2.62	0.009
D*J	21956	10978	136.2	80.59	0.000
D*K	-2312	-1156	136.2	-8.49	0.000
E*F	55	28	136.2	0.20	0.839
E*G	-138	-69	136.2	-0.51	0.612
E*H	1765	883	136.2	6.48	0.000
E*I	-3159	-1579	136.2	-11.59	0.000
E*J	-40	-20	136.2	-0.15	0.883
E*K	-229	-114	136.2	-0.84	0.401
F*G	1359	680	136.2	4.99	0.000
F*H	-470	-235	136.2	-1.72	0.085
F*I	62	31	136.2	0.23	0.820
F*J	2032	1016	136.2	7.46	0.000
F*K	1655	827	136.2	6.07	0.000
G*H	507	253	136.2	1.86	0.063
G*I	770	385	136.2	2.83	0.005
G*J	3262	1631	136.2	11.97	0.000
G*K	1452	726	136.2	5.33	0.000
H*I	-290	-145	136.2	-1.07	0.287
H*J	739	369	136.2	2.71	0.007
H*K	189	94	136.2	0.69	0.488
I*J	72	36	136.2	0.27	0.791
I*K	282	141	136.2	1.03	0.301
J*K	2037	1019	136.2	7.48	0.000

Analysis of Variance for Total (Coded Units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	11	1.06780E+12	1.0678E+12	9.7073E+10	8E+03	0.000
2-Way Interactions	55	2.06190E+11	2.0619E+11	3748909342	315.69	0.000
Residual Error	573	6804518214	6804518214	11875250		
Lack of Fit	61	5486407638	5486407638	89941109	34.94	0.000
Pure Error	512	1318110576	1318110576	2574435		
Total	639	1.28080E+12				

R^2 - 99.47%

Fractional Factorial Fit: Total Transportation Cost vs. A, D, F, G, J, K

Estimated Effects and Coefficients for Total (Coded Units)

Term	Effect	Coef	SE Coef	T	P
Constant		72244	300.7	240.28	0.000
A	-20447	-10224	300.7	-34.00	0.000
D	-67548	-33774	300.7	-112.33	0.000
F	-18029	-9014	300.7	-29.98	0.000
G	-18531	-9265	300.7	-30.82	0.000
J	-29126	-14563	300.7	-48.43	0.000
K	-10635	-5317	300.7	-17.68	0.000
A*D	-13050	-6525	300.7	-21.70	0.000
D*F	17585	8793	300.7	29.24	0.000
D*G	14331	7165	300.7	23.83	0.000
D*J	21956	10978	300.7	36.51	0.000

Analysis of Variance for Total (Coded Units)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Main Effects	6	1.05769E+12	1.0577E+12	1.7628E+11	3E+03	0.000
2-Way Interactions	4	1.86712E+11	1.8671E+11	4.6678E+10	806.77	0.000
Residual Error	629	36392490796	3.6392E+10	57857696		
Lack of Fit	53	16444647617	1.6445E+10	310276370	8.96	0.000
Pure Error	576	19947843178	1.9948E+10	34631672		
Total	639	1.28080E+12				

R^2 - 97.16%